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INFORMATION SYSTEMS EDUCATION JOURNAL

Editors

Using Constructive Alignment, eduScrum and Tableau to Teach Managerial Analytics

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Abstract

The research sought to study potential efficiency in course design and execution using Constructive Alignment, and then classroom workflow grounded in eduScrum based on the Agile Project Framework of Scrum for graduate classes in managerial analytics. The research measured performance based on the Scrum concept of Velocity, defined as the rate of improvement in learning as measured by the number of Constructive Alignments' Learning Objectives achieved. The process of class design creates a list of activities for each class that lends itself to a standardized learning workflow. Scrum, as a project framework originated within software development in the early 2000s, but has now become a managerial method of choice for projects in a wide variety of industries and sectors. The final product to be delivered is broken into increments of value that can be created by the team in short work periods, also called Sprints. EduScrum mimics the same approach, using each class session to act as a sprint in which the students are assigned to self-managed teams of students and assigned a list of learning activities to achieve. The teacher/professor's role shifts to coach, moving from team to team and improving workflow, overcoming barriers, providing resources, and ensuring each class maximizes value creation. Scrum and eduScrum rely on a short reflective learning session at the end of the Sprint, called a Retrospective, in which students and professors assess how they can improve the velocity of learning. Assessments are embedded for individuals as part of Constructive Alignment, and are connected to the Teaching/Learning Activities.

Keywords: eduScrum, Scrum, Agile, Constructive Alignment, Managerial Analytics

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Using Constructive Alignment, eduScrum and Tableau to Teach Managerial Analytics

Matthew Boyne

1. INTRODUCTION

The research for this paper began with the desire to craft a graduate class for organizational leaders on business analytics and data-driven decision making, that integrated the fundamentals of Agile Project Management in order to fully prepare students to lead a digital transformation in organizations. The paper describes a course design method, Constructive Alignment, to connect Intended Learning Objectives (ILOs) with specific Teaching/Learning Activities (TLAs). A teaching method known as eduScrum, which mimics an Agile Framework called Scrum (after the rugby term) was used to execute the TLAs and prepare the students for Assessment Tasks (ATs). For both data visualizations, data management and management of the class as an agile project the software Tableau was used. "Flipped", meaning outside class lectures, were recorded and added with guided readings for classroom preparation, freeing in class time to simulate project management with the ILOs acting as the work from an Agile Product Backlog (Tudevdagva, Heller, A., & Hardt. W., 2020).

The Mckinsey Global Institute (2011) highlighted the transformational potential of data. However, the report also highlights that turning data into information that can be acted on in a knowledge creating cycle requires actual transformation of the organization that precedes and anticipates technologies' opportunities. In order to execute data-driven strategies, agile management methods are needed given the uncertainty and rate of change (Brocchi, Brown, Machado & Neiman, 2016). Drawing from Mckinsey's studies, the course design needed to provide the necessary guidance to lead a data analysis effort using descriptive, predictive and prescriptive analytics while also acknowledging that the management of data requires a team of data scientists, data analysts, programmers and those with the necessary business/organizational expertise. Without understanding the context of the firm's problems in relationship to the data available, the process of data driven decision making will lack relevance to the organization.

Strategic organizational problems are too complex to solve without integrating decision-support systems, and the process of business analytics (Dewi, & Muniandy, 2014). The course was designed to prepare students to execute data projects with agile management in order to address organizational problems in areas such as supply chain, marketing, education, retail and healthcare as well as governmental problems such as homelessness using data analytics.

Previous work on the class design for data analytics courses tended to be focused on information systems management undergraduate majors, and have included visualization (Zhang, Chen, & Wei, 2020) with heavy emphasis on application of technology such as R, Microsoft BI and Tableau. Bacic, Jukic, Malliaris, Nesterov and Varma (2023) conducted a thorough literature review in their development of a graduate certificate supporting the dominance of analytical skills in academic programs that are highly valued by industry. Hartzel and Ozturk (2022) integrate non-resident expertise with industry experts as an integral part of their design studies, supplementing practical observations with the academic findings.

As part of the development for course content, 17 executives from the San Diego technology and life science fields were interviewed for their view of the necessary managerial skills for data analytics and digital transformation. The three top themes mentioned by each executive had to do with data visualization, data communication and team leadership skills. When asked what software skills they desired in their hires and managers 15 of the 17 stated they wanted people with knowledge of Tableau. Integration of agile management was only mentioned by 3 of the 17. Every interview specifically emphasized the need for data visualizations as descriptive analytics. The reason stated was the need to visualize the data as descriptive analytics. Only one executive expressed interest in enhanced forecasting methods found in regression analysis as predictive analytics.

From the study of literature on previous uses of eduScrum, and field interviews with executives, the course design was established to cover the following learning modules over a 14-week course:

1. Introduction to Statistics Fundamentals for Analytics Managers
2. Descriptive Statistics
3. Data Visualizations
4. Regression Analysis and Predictive Analytics
5. Prescriptive Analytics
6. Dashboard Design and Presentations

In order to ensure the required participation and accreditation limits of hours per week (7-8) were not exceeded, separate modules for agile management were not feasible. Rather than teach agile management methods separately, integration of the eduScrum as part of each class's Teaching/Learning Activities allowed students to learn agile project management by doing, and to apply team learning to the field of data analytics. Tableau can act as both a data visualization, and analytics tool, as well as a project management software for agile visualizations such as schedules, resources, burndown charts, budgets and risk.

2. EDUSCRUM AND SCRUM FRAMEWORKS

The motivation for organizations to use agile methods in complex situations is supported because of the flexibility in execution with the self-managed, and in many cases, autonomous high performing teams that are able to respond directly to customer demands (Sutherland, 2001; Sutherland & Sutherland, 2014; Schwaber & Sutherland 2012;2020). The agile methods are characterized by iterative and incremental value creation with collaborative engagements between stakeholders, customers, organizational leaders and teams (Neuman & Barham, 2021). As more users have adapted agile methods, and particularly the Scrum Framework, application has spread from software development to business, analytic, supply chain, healthcare, financial services and aerospace (Sutherland & Sutherland, 2014). Scrum as a framework has been used in teaching college classes in software engineering and product development (Lundquait, Ahmed, Friedman, Bernard, 2019). Mahic (2010) found most direct agile applications in class were in computer science, with one found in advanced mathematics.

The Scrum Framework, which eduScrum mimics, originated as a lightweight framework grounded in the Agile Manifesto as a way to generate adaptive solutions to complex problems (Schwaber & Sutherland, 2020; Sutherland & Sutherland, 2014). Grounded in empiricism, and applying the Lean Systems and Thinking from the Toyota Production System, the fundamentals of the framework drive ongoing process improvement, enhanced rates of learning and waste reduction (Wijnands, 2019; Wijnands & Stolze, 2020). The framework focuses on the essentials of people over processes, and collaboration over control. Using four formal events that are transparently open to all, and integrating inspection into the work along with adaptation to learning opportunities because of the self-managed teams yields a cycle of learning and continuous improvement.

The four formal events begin with the Sprint, a specific time frame consistently executed over the same duration, during which ideas on products are turned into accessible value for customers. The Sprint begins with planning, in which the team takes elements from a list of components or deliverables, the Product Backlog, and selects a manageable amount of work, the Sprint Backlog, that can be accomplished over the Sprint. The next event begins each workday as a Daily Scrum. This event acts as a daily brief, resource discussion and lessons learned from the previous day to keep focus on the definitions of value. The third event occurs after the Sprint and integrates stakeholders in a product increment review, along with Backlog adjustment. This is the Review and is product focus. The Review compares the product's value state with the expectation of the stakeholders. The last Scrum event looks at the workflow and processes from the perspective of effectiveness, and the team dynamics that offer learning opportunities. The Scrum Retrospective studies the rate of change of the learning, called the velocity so as to quantify the team's performance and improve (Brown, et.al., 2019).

Within the Scrum Framework there are three roles. The Product Owner creates and manages the Product Backlog determining value creation of product quality performance specification. The Product Backlog is an ordered definition of work that needs to be accomplished and represents what the customers have described as a usable product. The Scrum Master is the leading advocate and facilitator for establishing Scrum throughout the organization and facilitating the team dynamics within the Scrum Framework. The Scrum Master is a team coach and leader that serves removing impediments from team learning. The Developers are the team and hold themselves accountable for the value creation. The Developers determine what work can be accomplished in each Sprint, in consultation with the Scrum Master and Product Owner (Williams, 2010).

The key artifact for the Scrum Framework is the Product Backlog which lists specific components, processes, tasks, products, communications, and relationships that come together to meet the customers' needs. When filtered by the team down to what can be accomplished in the next Sprint, the Sprint Backlog becomes the incremental addition of value using the lessons from previous Sprints to refine products and processes. (Otero, et al., 2020).

EduScrum adapts the roles, events and artifacts into a classroom environment (Wijnands, 2019; Wijnands & Stolze, 2020). The teacher takes a combined role of Product Owner and Scrum Master, possibly sharing the Scrum Master duties with a student as a Team Captain, depending on professor preference, and class maturity. The Product Backlog is a listing of learning objectives represented as teaching and learning activities, broken down into Sprint Backlogs. EduScrum is often established with seven-week Sprints, though other researchers have used durations from two to four weeks.

Rush and Connolly (2020) emphasize the soft-skill development opportunity for students when integrating Scrum into the learning process. The students are required with the Restrospective opportunities to critically reflect and de-brief overall team performance bringing aspects of conflict resolution, negotiation and team-mate development into the analytics classroom. Linden (2018) adds to the human factor with research that details positive student responses to the opportunity for self-regulated learning using Scrum in a classroom. The students highly preferred working in a Scrum environment in which they had control over how they learned as compared to lecture-based classes. Magana, Seak and Thomas (2018) reported the constant feedback from the periodic Retrospectives and Reviews was found to be beneficial by students; and preferred to traditional quizzes as a way to assess learning.

EduScrum measures the rate of learning with a Run Up Chart tracking learning objectives given a quantitative value over Sprint duration allowing assessment of the velocity of the students' learning. The Run Up Chart is the same as a Burndown Chart in Agile Project Management, a tool to measure velocity of learning. The measurement of velocity, or student learning was the key measure for performance in this type of research (L´opez-Alcarria, Olivares-Vicente, & Poza-Vilches, (2017). Appendix A contains Figure 1, a commonly used class work board to visualize the eduScrum flow from ILOs in the form of Sprint Backlog (Blickharz, 2021).

3. COURSE DESIGN WITH CONSTRUCTIVE ALIGNMENT-LEARNING OBJECTIVES AND TEACHING/LEARNING ACTIVITIES

Shuell (1986) describes the teacher's fundamental task as motivating students to engage in learning activities that build into desired learning objectives for the course, because of effective design. What the student does to achieve the objectives through the activities is more important than what the teacher says or does. Constructive alignment engineers the classroom as a method of outcomes-based teaching (Biggs & Tang, 2011). The design of the course moves from the end state of all learning objectives (Intended Learning Objectives) being executed through class Teaching/Learning Activities (TLAs) followed by the demonstration of competency in Assessment Tasks (ATs). Biggs (2014; 1993) emphasizes that careful construction of content specific ILOs that are achieved because of the TLAs, and then how they are assessed with the ATs accomplishes Schuell's guidance to focus on what the students are doing, rather than the teacher's actions. There are four stages for Constructive Alignment course design:

1. Describe the ILOs using activity verbs
2. Create a learning environment with TLAs using the activity verbs
3. Use ATs to assess student performance using the activity verbs
4. Translate the performance into standardized grading criteria

Biggs (2014) and Biggs and Tang (2011) emphasize the importance of verbs in Constructive alignment. The same verbs, that are found in the ILOs and represent the requisite level of Bloom's Taxonomy for the class level should also describe the same action in the TLAs and well as what will be assessed in the ATs.

Class Organization

Beginning with Constructive Alignment, and in order to create ILOs, seven business analytics text books were reviewed seeking ILOs that were common in the support material, and emphasized by the authors in the provided lectures and teaching notes. This review provided a list of seventeen potential learning objectives. Peer universities as described as liberal arts universities in the Southern California region, that offered graduate level analytics classes were contacted. In the area, those that have an evening MBA or MS program for working adults, but also have traditional undergraduate programs dedicated to liberal arts revealed seven candidate universities. The seven all had analytics classes designed primarily with a data management foundation and focused on communication, leadership, team development, fundamental statistics, visualization and data-driven decision making, rather than a data science/information systems primary focus. Each of the seven colleges was contacted and the faculty were kind enough to share their learning objectives. The seventeen potential learning objectives from the textbook were reduced to seven. This list was reduced to the following six in order to manage each ILO being achieved in two-week Sprints.

Intended Learning Objectives

1. Create data visualizations describing organizational performance using financial, human resource, operations/supply chain and customer feedback key performance indicator data.
2. Derive insights from data that translates to creating organizational improvement projects using gaps in performance with Key Performance Indicators.
3. Design effective data reports describing organizational problems and opportunities.
4. Predict effective outcomes using regression analysis based on organizational data.
5. Apply data driven decision making to organizational performance gaps and communicate outcomes in a data report integrating ethical decision making as well.
6. Create a dashboard as an Executive Support Systems using the Balance Scorecard Framework

The ILOs became the Product Backlog for the semester with Week 1 dedicated to an introduction and practice session. Weeks 2-7 were broken into separate Sprints for each ILO, followed by a Midterm in Week 8, and then more Sprints for Weeks 9-14. An Individual Assessment Task was assigned as a Final. In order to focus the classes on the Sprints the classes were “flipped,” with videoed lectures on guided readings and explanation of the deliverables for the Learning Objectives. The classroom itself was managed as a Scrum, with a Sprint Backlog creation, Daily Scrum, and at the end of the class a Sprint Review with a Retrospective. The teacher/Product Owner explained the Teaching/Learning Activities necessary to succeed with the ILOs during the “flipped” lectures, as well as during the Daily Scrum. The TLAs were connected to specific parts and problems within the text that built towards the ILO and Product Backlog.

At the start of class students were divided into teams of five or six students. This allowed each class to have four or five teams working, while also fitting into the physical constraints of the classroom layout. The rubrics used for each of the deliverables that derived from the Individual Learning Objective (ILO) was the connection from the ILOs, to the Teaching/Learning Activities (TLAs) and then the grading of the deliverable as the Assessment Tasks (ATs) in order to maintain the flow for Constructive Alignment.

As an example of the eduScrum work from class along with the Constructive Alignment process, and using the “Design effective data reports describing organizational problems and opportunities” ILO, the TLAs for a two-week Sprint was presented in an eduScrum Sprint Backlog with the following items using a real estate data set of home sales. The report from the Spring became the Assessment Task for the team:

1. Find the mean and median home price for the five areas and state them in a table. What are the outliers? What is the effect of the outliers?
2. Create a visual analytic describing the average home prices.
3. Find the average square footage by city and state them in a table. What are the outliers? What are the effects of the outliers?
4. Create a visual analytic describing the square footage by city.
5. Create a visual analytic showing a comparison of the square footage and the home price for each city.
6. Find the average lot size for each of the five cities and state them in a table.
7. Create a create a visual analytic showing the average lot size for each city.
8. Create a visual analytic showing the three variables for each city of average price, average square footage and average lot size.
9. Using these analytic results create a 3-page report summarizing the results and embed the visualizations. What area should be considered for future real estate investments? Why?

4. USE OF TABLEAU

Given accessibility, intuitive use, a graduate demographic that tended more towards non-technical and quantifiable undergraduate majors; along with superior user support, Tableau was chosen as the primary analytics and visualization software. R was experimented with in each class but without exception students preferred using Tableau for analysis and visualization. Excel was partnered with Tableau, so as students would create a visualization or solve a problem in Tableau, the same result had to be achieved with Excel. In some applications, such as complex linear regression for predictive analytics or the Monte Carlo Simulation for prescriptive analytics only Excel was used given limitations in Tableau.

Tableau was also used as project management software to create Gantt Chart schedules, assign and level resources, manage the burndown of the ILOs, along with simulated budgets and earned value management problems. The Tableau visuals that were applied to each ILO and the project management worksheets were managed together in a single Tableau workbook. Tableau was embedded into each class as part of the Sprint, use of Tableau videos from the student resources were assigned as part of the flipped class.

5. RESULTS

Each Sprint for the Product Backlog was given a "story point" or user value of 7.5% of the grade, or 45% overall. The midterm and final made up 35% and two short individual case studies contributed the final 20%. A burndown chart was created beginning with 450 (out of a total of 1000 for the class) points and a linear line descending over each Sprint. Five semester-long classes, the first two in Summer 22, one in Spring 23 and one over Summer 23 have been run. The total number of students in these classes was 107 students. Lessons from each Retrospective and Review have been applied, along with feedback from end of course evaluations.

Classes Summer 21

The first Sprint resulted in 45 and 50 points achieved out of the possible 75 in the first Sprint. During the Retrospective students gave feedback that the into lectures in the classes were too long and did not add value since I was repeating what the "flipped" lecture provided. The process was changed to a 15-minute Scrum Plan, primarily focused on the rubric so students would have clarity as to the deliverable. The velocity increase to 80 points in the second sprint, then 120 and 125. The Individual Learning Objectives were complete in Week 12, allowing a Week for integration of a guest lecturer from industry. The two classes of 57 students also returned high assessment grades on the class for team dynamics, leadership, quantitative knowledge and decision making. The professor assessments resulted in an overall grade of 4.7 out of 5. Particular attention was placed in the Sprint Retrospectives on the clarity, quality and thoroughness of the rubrics to ensure students understood and applied the elements towards the quality standards for the deliverable. A specific question was inserted into the Professor Review asking about the quality of the rubrics. All 57 students responded that the rubrics showed the alignment between the ILOs, the TLAs and the ATs.

Classes Spring and Summer 23

More emphasis was placed on the "flipped lectures over the first two weeks concerning the underlying set up for visualization. End of course feedback from the previous classes had indicated clarity was needed on the specific way the quantitative and qualitative data had to be placed in order to create the proper visualization. The root cause of the delays in the first two Sprints' productivity was understanding how certain charts were needed for certain types of statistics. As an example, a Line Chart tends to work best with time phased data, such as budgets. Bar Charts work well with Categories and Numerical data. By closely relating the types of charts to the types of data the velocity of the Sprints improved by 30% over the first three weeks completing the ILOs by Week 12 and freeing up additional time an additional public policy case study. The student reviews of the professor for these classes resulted in a slightly higher score of 4.8 out of 5.0 for the 50 students. The same 100% response rate on the importance of clear and through rubrics was received highlighting that aspect for effective Constructive Alignment.

In order to additionally quantify the opportunities in using eduScrum as a way to improve the teaching of analytics, data was collected from a standardized Statistics exam that each MBA student had to take as part of their Analytics class. The test is from Peregrine, a company that specializes in levelling modules for students in graduate programs that may not have had an undergraduate class in basic statistics. Prior to the summer of 2021 and eduScrum, 294 students had taken the test with an average grade of 82 and a median of 87, showing some significant low scores. The failure rate was 12%. The Module had been given after computer-based work in the second week of class. In the first class run, the Module was moved to Week 13 and each week a short eduScrum Sprint of about 20 minutes was dedicated to working through the basics of Statistics. The average moved to 88 with a median of 89 for the 107 students. The failure rate dropped to 3%.

6. LIMITATIONS AND FUTURE DIRECTION

The method of merging the Scrum roles of Scrum Master and Product Owner into the eduScrum class assumes the professor/teacher is comfortable managing Agile Projects, or receives significant training to function in those roles. Project Management development classes often take 40 hours of in class work with 80 hours expected outside of class. In cases such as this research the method was intuitive because the researcher had spent 15-years leading agile teams and had performed roles of Product Owner and Scrum Master in dozens of actual projects. For a professor not having that background initial study time may prove prohibitive.

Future opportunities for this class process will focus on the integration of Artificial Intelligence that Tableau is being equipped with. Future research will seek to employ these Agile classroom methods while at the same time seeing how AI can enhance analytics with human-system integration.

7. CONCLUSION

Constructive Alignment in course design can be used to create a Product Backlog and subsequent Sprint Backlogs for eduScrum classrooms. The key for execution in each Sprint is a clear and thorough rubric. The ongoing classroom improvements motivated by the students' own rigorous Sprint Retrospectives increased the velocity of learning and completed the ILOS ahead of schedule allowing additional topics to be brought in. eduScrum teaches both the subject of the class, and the leadership methods, communication, and team dynamics for projects.

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Appendix A
Figure 1

Source: eduScrum library

Figure 1: Sample class work board to visualize the eduScrum flow from ILOs in the form of Sprint Backlog

An Experiential Learning Approach to the Introduction to Business Course

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Abstract

This paper presents the results of a multi-year effort to redesign the introduction to business course at Western Michigan University. ScrimmageSIM, a business simulation that emulates commercial ERP systems, provides the core experience in the course and is a mechanism for students to develop their understanding of business with a focus on quantitative analysis. The design and implementation of the simulation experience follows the experiential learning spiral, as students run the simulation five times with increasingly complex scenarios. The overall design of the course is competency-based, as students have the opportunity to redo many of the course assignments to earn a better grade. The simulation experience, combined with the competency-based design of the course, has resulted in a more rigorous course with students earning grades that are better than they were with the previous curriculum.

Keywords: Business Simulation, Experiential Learning, Introduction to Business, Competency-Based Education

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An Experiential Learning Approach to the Introduction to Business Course

Bret Wagner and Melissa Intindola

1. INTRODUCTION

Borden (2016) compared introduction to business courses at 17 top-ranked business schools (see Appendix A). This comparison suggests that there is not a consensus on what should be taught in an introduction to business course—or even if there should be one. In the fall of 2020, the Haworth College of Business at Western Michigan University (WMU) made the decision to redesign their introduction to business course. This change was prompted by a restructuring of the university's general education requirements. Appendix B compares the previous general education curriculum with the new Essential Studies curriculum. Among the improvements made to this curriculum was a "laddering" of the requirements so that there was not a tendency for students to complete all of these requirements in their freshman/sophomore years. The new curriculum had learning objectives defined for each category, and a curriculum proposal was required for courses to be included in the new Essential Studies curriculum. These proposals required a detailed assessment plan to show how the course would meet the learning objectives for the category, and an organizational structure was established to review Essential Studies courses on a regular basis.

The existing introduction to business course, BUS 1750 - Business Enterprise, qualified for the previous General Education requirements under Area V, Social and Behavioral Sciences. The new WMU Essential Studies curriculum did not have this, or a similar, category. To avoid adding additional credits to the degree requirements for all business students, it was necessary to find a "home" for the introduction to business course in the new WMU Essential Studies curriculum. After review, the category Oral and Digital Communication was identified as the best opportunity for this course to be included in the WMU Essential Studies program.

Courses in the essential studies curriculum must be accessible to students from a variety of majors. WMU is a comprehensive university with over 150 majors, and many of the students in this course, especially in the spring semester, are not business students. The revised course was designed to provide a good foundation for business majors to build on as they progress through the curriculum, and for non-business majors many will work in for-profit organizations, and the concepts covered in the course are valuable those who will work for-profit and in not-for profit organizations.

Three goals were set for this redesign of this course:

1. Meet the new WMU Essential Studies Requirement for Oral and Digital Communication
2. Make the course more experiential in nature.
3. Improve the quantitative literacy of students.

The vehicle for achieving these goals in the course redesign was the ScrimmageSIM business simulation that was developed by the lead author. At this time the ScrimmageSIM simulation was not only used in several courses at WMU but also at a handful of other universities in a variety of courses.

ScrimmageSIM was designed to replicate Enterprise Resource Planning systems like SAP and Oracle, which provides two advantages:

1. A student experience that mimics the type of enterprise systems students will see in industry.
2. A configuration capability to facilitate the simulation of different businesses and business scenarios.

Using the ScrimmageSIM simulation would not only provide the experiential learning component of the course but wouild also evolve to address several challenges in deploying this course to over 1,100 students annually.

In addition to providing the experiential learning component of the course, ScrimmageSIM also supported the goal of quantitative literacy. The concept of quantitative literacy used to revise BUS 1750 consisted of two components: the application of mathematical models to business problems, and the analysis of financial statements to understand a business.

This goal would be difficult to achieve with the current generation of introduction to business textbooks. Appendix C shows the chapters for three current introduction to business textbooks from Pearson Publishing, and Appendix D shows the chapters for two current introduction to business textbooks from McGraw-Hill. While the design of introduction to business courses is varied, the content of all five textbooks is quite similar. All five books cover Ethics and Global Business within the first four chapters, even though students will not have a very deep understanding of business when reading these chapters if the instructor assigns chapters in the order in which they appear in the table of contents. All five also postpone the discussion of accounting and finance topics until the end of the book, and then cover the topic in a cursory fashion. Because of this, the current set of introduction to business textbooks proved unsatisfactory to achieve the goal of quantitative literacy.

Thus, the lead author began work on Fundamentals of Business, a textbook that is sold as an Amazon Kindle textbook for $9.99. Not only is the textbook be affordable, but because the Kindle Application is available for computers, tablets, and cell phones, it is easier for students to read as it is be readily available when the student has a few spare minutes. The simulation cost was $99 per student, which included grading of two papers and a presentation, which is discussed later. The total cost of course materials was approximately two-thirds of the previous course materials.

Table 1 shows the chapters of Fundamentals of Business used in the revised course. Chapter 2 – Generating profits covers the income statement. The chapter does not cover the construction of the income statement using debits and credits, but rather, presents the completed income statement and shows how the information provided can be used by managers to understand the business.

Chapter 3 – Assets of the Firm, covers the balance sheet and Chapter 4 – Managing Cash, covers the statement of cash flows. A major focus of these chapters is how to use financial ratios to understand the performance of a business.

Chapter 14 – Business Financing, provides significant coverage of discounted cash flows, which is emphasized in the course. Chapter 25 – Personal Financial Planning, builds on the discounted cash flows covered in Chapter 14 to provide concrete examples on long-term financial planning. Simple quantitative models were included as much as possible in other chapters, for example, the lifetime customer value formula is presented in Chapter 7 – Marketing: Providing Customer Value.

Chapter 1 – Introduction
Chapter 2 – Generating Profits
Chapter 3 – Assets of the Firm
Chapter 4 – Managing Cash
Chapter 8 – Leadership in Business Organizations
Chapter 5 – Economics
Chapter 6 – Introduction to Business Strategy
Chapter 14 – Business Financing
Chapter 7 – Marketing: Providing Customer Value
Chapter 15 – New Product Development
Chapter 10 – Supply Chain Management
Chapter 25 – Personal Financial Planning

Table 1 – Chapters from the textbook Fundamentals of Business

To further the quantitative literacy of students, spreadsheets are integral to the course. There are two problems that must be addressed to ensure that students learn from spreadsheet assignments. The first one is well known: cheating. This issue was addressed by creating a security macro in Excel that does two things.

First, the student must enable the macro and type their name in a pop-up window before working on the spreadsheet. This macro saves their name to a password protected sheet so that each student must create their own spreadsheet. To close the loop, the macro also disables the paste function in Excel, so that the results from one spreadsheet cannot be pasted into the macro-enabled spreadsheet. Thus, the only way for a student to submit someone else's work is to have the other person create a complete spreadsheet for the student.

The other issue with spreadsheet assignments is that students may perceive the spreadsheet as an additional, non-value-added step if the spreadsheet is not actively used in the class. If a student is presented with a concept in class and given an assignment to build a spreadsheet that incorporates that concept but never applies the spreadsheet to solve a realistic problem, they are much less likely to see spreadsheets as a tool. To address this problem, students are provided with pre-built planning spreadsheets which they must use to develop plans that they will execute in the simulation. This use of spreadsheets helps the students see the value of spreadsheets as a tool. An expanded security macro is used for these spreadsheets that logs every student input so that it can be determined whether the students used the spreadsheets in a trial-and-error fashion to develop their simulation plan.

2. INTEGRATION OF SCRIMMAGESIM

Using a simulation in a course does not, in and of itself, create engagement or, more importantly, learning. As David Crookall noted, "simulation/games can generate strong feelings (both positive and negative) during play. They may include frustration, anger, satisfaction, accomplishment, desire to win, group belonging, new identity, pleasure, overwhelmed by complexity, cognitive dissonance, and so on." (Crookal, 2014). He pointed out that these emotions, especially the negative ones, can get in the way of learning and "can only be addressed (and defused) in the debriefing, not in the thick of the action of the simulation/game." This is partially true, in that the debriefing may not be able to fully address negative emotions if a student performs poorly and has no option to improve. Furthermore, if the simulation is just a one-time experience, there may be limited motivation to engage fully in the debrief.

These problems can surface even when a simulation is a continuous component of the course, for example, a strategy simulation in a capstone course. If a team performs poorly in the first period of a semester-long simulation, it may put them in a situation where they will need to work very hard for the rest of the semester just to end up with a mediocre grade.

ScrimmageSIM was designed to address these issues. The ERP design of the simulation allows for the creation of a set of increasingly difficult simulation scenarios using the same company. Poor performance on one scenario has no impact on the performance in the next scenario. In addition, the simulation was structured so that students could rerun the simulation on their own to earn a better score while simultaneously increasing their understanding of the scenario and preparing them for the next simulation scenario. Example screens from ScrimmageSIM are shown in Appendix E.

The simulation experience and debrief can be viewed as two parts of Kolb's experiential learning model (Kolb, 1984). Figure 1 illustrates Kolb's experiential learning model. The simulation is the concrete experience and the debrief is the reflective observation. Learning from these two steps is enhanced if this is followed by abstract conceptualization and active experimentation. Furthermore, the learning can be enhanced by repeating the four steps of the experiential learning model, which Kolb and Kolb (2012) describe as the experiential learning spiral. In BUS 1750, students run the simulation five times, which provides for an experiential learning spiral experience. Details of these simulation runs are shown in Appendix F.

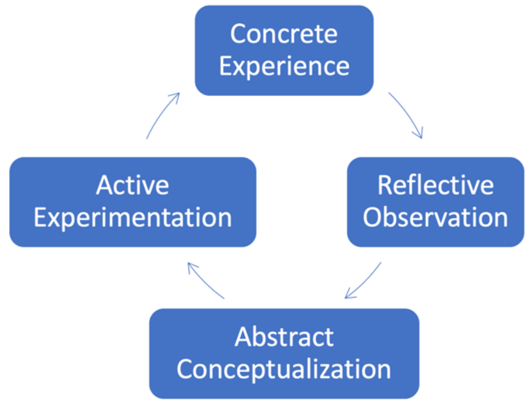

Figure 1 – Experiential Learning Cycle

Prior to running the simulation for the first time, students review two videos: one describing the simulation environment for Scenario 100 and one describing the operation of the simulation.

The simulation environment is a small brewery that produces three beers using four fermenters, which are the bottleneck operation of the production process. Students operate the simulation for one simulated year, and in the first scenario they only need to decide what product to make on each of the four fermenters. In the scenario, there is a summer beer with high demand from April through August. The demand in these months exceeds the facility's capacity, which provides the challenge in the simulation. Students must produce a written paper that summarizes the information provided in these two videos in a format that should be useful during the first simulation run.

The simulation is run using teams of three students during class time to leverage competition in increasing engagement. Despite writing a paper describing the simulated environment and simulation operation, students may not perform well on the first simulation. Even with an effective debrief, students may be frustrated by their performance and miss the benefits of reflective observation. BUS 1750 employs two mechanisms to counteract this: the ability to rerun the simulation outside of the classroom and earn a better score, and they fact that they will run Scenario 100 again in class (after developing plans) as well as three others that build on the fundamentals introduced in Scenario 100. To support this course, a well-staffed tutoring center is provided where students can receive individualized help when rerunning the simulation.

In addition to being able to rerun the simulation, students also are guided in reflective observation on a variety of topics.

For example, after the first run of Scenario 100 there is a discussion on cost absorption. Many students assume that they should run the inventory to zero by the end of the simulated year. During the first run of Scenario 100 they are advised not to do this. In the class after the simulation, the basics of cost absorption and its impact on earnings before tax is explained so they will understand why they should not run the inventory down to zero in the simulation as well as the the reason cost absorption may cause companies to engage in "channel stuffing" to improve the income statement in the short run in spite of the long-run negative impact.

To provide an opportunity for students to engage in Abstract Experimentation and Active Engagement, students are provided with a planning spreadsheet to use in developing a plan for their second run of Scenario 100. An example of this spreadsheet is shown in Figure 2. This spreadsheet helps them understand theuse of spreadsheets as a tool, and exposes them to more advanced spreadsheet capabilities like conditional formatting. In the simulation, each batch of beer requires 14 days to produce. The planning spreadsheet is designed with monthly production quantities to simplify the problem.

AN34

ARBORCREST ALE STUDIOS

Taj Mahal

Price = $17.50
Cost = $10.43

	Forecast (CS)	Beginning Inventory (CS)	Production (CS)	Available for Sale (CS)	Sales (CS)	Lost Sales	Ending Inventory (CS)	Gross Profit
Jan	3,489	5,873	4,000	9,873	3,489		6,384	$24,667
Feb	3,525	6,384	4,000	10,384	3,525		6,859	$24,922
Mar	3,561	6,859	4,000	10,859	3,561		7,298	$25,176
Apr	3,596	7,298	4,000	11,298	3,596		7,702	$25,424
May	3,632	7,702	4,000	11,702	3,632		8,070	$25,678
Jun	3,668	8,070	4,000	12,070	3,668		8,402	$25,933
Jul	3,704	8,402	4,000	12,402	3,704		8,698	$26,187
Aug	3,739	8,698	4,000	12,698	3,739		8,959	$26,435
Sep	3,775	8,959	4,000	12,959	3,775		9,184	$26,689
Oct	3,811	9,184	4,000	13,184	3,811		9,373	$26,944
Nov	3,847	9,373	4,000	13,373	3,847		9,526	$27,198
Dec	3,882	9,526	4,000	13,526	3,882		9,644	$27,446
							TOTAL =	**$312,699**

AliCat

Price = $15.50
Cost = $10.08

	Forecast	Beginning Inventory (CS)	Production (CS)	Available for Sale (CS)	Sales (CS)	Lost Sales	Ending Inventory (CS)	Gross Profit
Jan	553	2,564	5,000	7,564	553		7,011	$2,997
Feb	1,280	7,011	5,000	12,011	1,280		10,731	$6,938
Mar	2,527	10,731	5,000	15,731	2,527		13,204	$13,696

Figure 2 – Scenario 100 Planning Spreadsheet

Part of the abstract conceptualization is to understand how complex business problems are frequently simplified to make them manageable, but that this creates a challenge in implementing the results of the simplified model. Many times in the course students are reminded of George Box's saying that "all models are wrong—some are useful."

Finally, active engagement is achieved by having students submit their planning spreadsheet for a grade. The planning spreadsheet incorporates a security macro that makes sure that their name is saved to a password-protected sheet, the paste function is disabled, and a log is kept of every change to a decision cell. In the Scenario 100 version, students make production decisions for two of the three products, and any remaining capacity is allocated to the third. Conditional formatting alerts students if their schedule is infeasible because they scheduled more production that the available capacity. The spreadsheet grade is comprised of three components: is the proposed schedule of production feasible, does the plan generate an earnings before tax (EBT) value that exceeds a minimum target, and does the log sheet indicate that students have met a minimum number of trial-and-error entries?

Planning spreadsheets are modified to incorporate additional features in each scenario, reinforcing their abstract conceptualization of the simulation environment. Active experimentation occurs both when they build their spreadsheet plan and when they present their spreadsheet to their team and develop a team spreadsheet and execution plan in a required team planning meeting. Students record the team planning meetings using Microsoft Teams. Instructors review these team meeting videos and provide feedback to students on their participation in the meeting. If a student continues to be unprepared for team meetings and does not participate effectively, teams are shuffled, and a non-performing team member may become an "individual performer." This does not happen often, and it usually happens when a student has completely disengaged from the course and does not respond to emails. In this case the instructor files a student concern form so that Student Academic Affairs can follow up on the student.

Teamwork is also emphasized in the lecture on Leadership in Business Organizations, which includes an in-class group exercise on personality types and the impact this has on their participation in their team.

3. COMPETENCY-BASED DESIGN

Much of the focus in competency-based education is on the entire educational institution, and includes topics such as curriculum processes, institutional resources, financial aid, role of the faculty, etc. There is not a single agreed-upon definition of competency-based education, but the one offered by the Competency-Based Education Network aligns with the philosophy used in the development of this course:

> Competency-based education combines an intentional and transparent approach to curricular design with an academic model in which the time it takes to demonstrate competencies varies, and the expectations about learning are held constant. Students acquire and demonstrate their knowledge and skills by engaging in learning exercises, activities, and experiences that align with clearly defined programmatic outcomes. Students receive proactive guidance and support from faculty and staff. Learners earn credentials by demonstrating mastery through multiple forms of assessment, often at a personalized pace. (Stewart 2021)

Withing the restrictions of a college course in a traditional educational environment, BUS 1750 was designed to give students as much time as possible to develop mastery. The ability to rerun simulations is one aspect of the competency-based design approach used in the development of the course. The mid-term and final exams are both formative and summative. These exams are online and taken by the student outside of the classroom. There are two versions of each quantitative problem with randomly generated problem values. True/false and multiple-choice questions are randomly selected from a larger bank of questions. The midterm exam is available at the beginning of the semester and allows for multiple attemps with the best score counting. There are no practice problems for quantitative topics. Students are encouraged to attempt the questions related to each topic in the exam after it is covered in class, providing a formative assessment of their learning. The students grade for the midterm is determined by their best performance on the exam, providing a summative assessment of the material covered. For the midterm exam, there are four weeks between the time all of the material in the exam is covered in class and when the exam is due. A similar structure is used for the comprehensive final exam.

The course has two written assignments: A report that summarizes the information provided to run the first simulation scenario and a detailed company report that includes an analysis of the company's financial statements.

To moderate the additional teaching workload, grading of the two papers is outsourced to a team of writing professionals via ScrimmageSIM. Student papers are submitted as PDF files via the simulation. The graders are provided with iPads and iPencils, so they can write comments on the student's PDF file. Graders assign the score based on the detailed rubric and can also provide summary comments. Continuing the competency-based design, students are encouraged to take the feedback, revise their assignment, and resubmit their paper for a better grade. In addition to reducing the instructor workload and providing students with an opportunity to learn by revising their work, this system provides quicker, more detailed, and more consistent student feedback.

In addition to being able to resubmit the two paper assignments, students can also resubmit two spreadsheet assignments—the first involves building a spreadsheet to calculate their grade in the course and the second one to calculate gross margins. Late assignments are accepted in most cases with a 10% late penalty to encourage students to work in a timely fashion yet allow them to be successful if they make mistakes in time management. The exception to this late submission policy is the simulation planning spreadsheets and planning meetings, which must be completed prior to the simulation sessions for students to take full advantage of the experiential learning component of the course.

4. PRELIMINARY FINDINGS

During the development of the course there was much concern on the part of many faculty members that it would be too hard for students. This turned out not to be true. Figure 3 shows that students performed better with the new curriculum than with the old curriculum, even considering the impact of Covid on freshman student's high school education in the Spring 2023 classes. Spring 2019 was used as the comparison group because the composition of students in the spring semester is approximately 2/3 non-business students and 2019 was the latest semester of the old curriculum that was not impacted by Covid. There were 551 students in the course in Spring 2019, and 416 in Spring 2023. Two major reasons that students were able to do well with a more challenging curriculum was the ability to resubmit many of the assignments and the staffing of a tutoring center for the course.

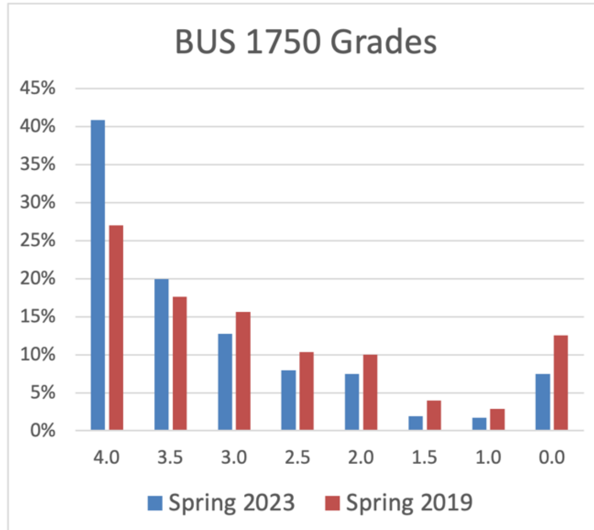

Figure 3 – Comparison of Final Grades

To better understand how well the course was performing, students were given a detailed end-of-semester course evaluation. Extra credit was given for completing the survey, which resulted in 330 of 416 students completing the survey, which is a 79% response rate.

Again, the simulation was designd to provide a spiral of learning experience, and teamwork was designed to be a critical component of this spiral. Two questions in the survey were geared to finding out if these simulation components of the course were successful. Figure 4 shows the response to the question "The simulation exercises helped me to be more engaged in the course," and Figure 5 shows the response to the question "Working with fellow students in my team contributed to my learning in this course."

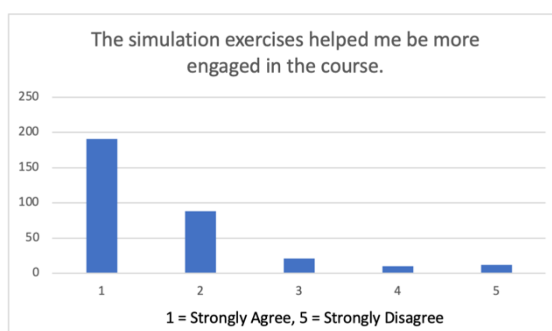

Figure 4 – Simulation and Engagement

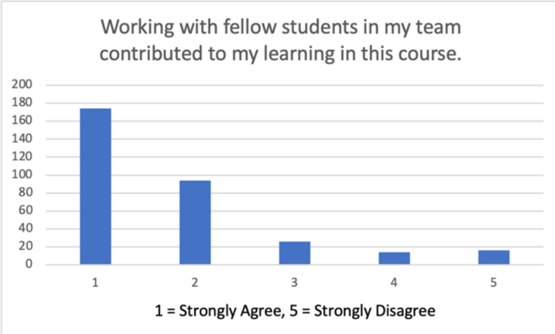

Figure 5 – Teamwork and Learning

These results show that 83% of students agreed or strongly agreed that the simulation helped them be engaged in the course. The use of teams for planning and execution of the simulation resulted in 87% of the students agreeing or strongly agreeing that working with fellow students contributed to their learning.

Because students participated with their teams in class and submitted recorded meetings, students were unable to be "free riders" without it being noticed. The authors feel this contributed to the strong survey response on the value of teamwork. Hopefully these students will be more likely to actively participate with teams in their future classes.

Four class sessions at the beginning of the course are devoted to understanding financial statements. Students also produce a company analysis paper which includes analyzing the company's financial statements. In addition, accurate financial statements are a key feature of ScrimmageSIM, and there are a number of points where the simulation financial statements are used in reflective observation to inform key course concepts. Figure 6 shows the results for the question of how satisfied students were with their ability to analyze financial statements. While not as strong as the results for the value of the simulation and teamwork, 75% of the students were extremely satisfied or satisfied with their ability to analyze financial statements. Hopefully this experience will result in better performance in accounting classes for these students.

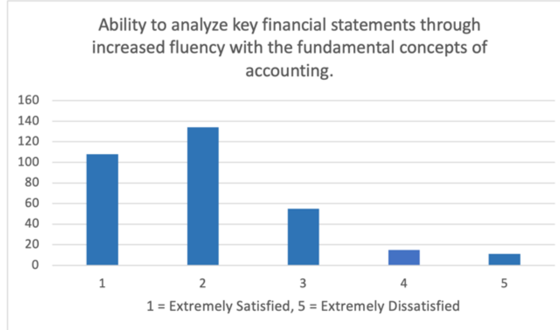

Figure 6 – Analyzing Financial Statements

A single-factor ANOVA was performed to determine the impact of the instructor on the question of student satisfaction with their ability to analyze key financial statements. The result of this analysis showed that the impact of the instructor was statistically significant with p = 1.77e-7.

The course survey was designed as an exploratory survey, however, three different regression analyses were conducted to look for other factors that influenced student learning.

In the first, we regressed the degree with which students reported that "The simulation exercises, including the pre-simulation work, helped me learn to use Excel as a problem-solving tool" onto the students' "… fundamental understanding of economics and how economic concepts can be used to better understand the business environment." In this model, adjusted R^2 was .28, indicating that approximately 28% of the variation in student's understanding of economics and the application of economic concepts to business could be explained by the simulation exercise. The model was significant at the .05 level, but this R^2 value is widely considered 'weak' (Srinivasan, 2020).

In the second model, we regressed student's assessment of whether "The instructor was knowledgeable about the operation of the simulation and could answer student questions about how the simulation worked" onto the students' "… fundamental understanding of economics and how economic concepts can be used to better understand the business environment." In this model, adjusted R^2 was .30, indicating that approximately 30% of the variation in student's understanding of economics and the application of economic concepts to business could be explained by perception of the instructor's knowledge of the simulation and ability to answer questions about the simulation. The model was significant at the .05 level, and adjusted R^2 is at the bottom of the 'moderate' range for explanatory value (Srinivasan, 2020).

In the third model, we utilized a multiple regression approach, regressing the instructor's knowledge and ability to answer questions ("The instructor was knowledgeable about the operation of the simulation and could answer student questions about how the simulation worked") and students' assessment of the simulation tool ("The simulation exercises, including the pre-simulation work, helped me learn to use Excel as a problem-solving tool") onto students' "… fundamental understanding of economics and how economic concepts can be used to better understand the business environment." In this model, adjusted R^2 was .39, indicating that approximately 39% of the variation in student's understanding of economics and the application of economic concepts to business could be explained by perception of the instructor's knowledge of the simulation ***as well as*** the simulation exercise. This model was significant at the .05 level, and is reporting at a level well into the 'moderate' range (.3-.5) of explanatory power (Srinivasan, 2020).

In Scenario 200 and beyond, students were able to adjust prices so that they could align demand with capacity and increase their gross margins. The course spends three classes covering economics: one class on supply and demand, one class on price elasticity, and one class on economic systems (free market economies, socialism, and communism). In addition to discussing elasticity in class, elasticity is implemented in the planning spreadsheet for Scenarios 200, 220 and 230. Because elasticity is not only discussed as an abstract classroom topic but implemented in a planning spreadsheet prior to being a crucial part of three simulations, it makes sense that students feel the simulation helps them understand the relationship between economic concepts and business.

These three regression models were the only models that showed instructor experience had an impact on learning key topics. That instructor experience was not shown to impact the student experience more is not surprising as all instructors share common teaching materials including classroom PowerPoint slide decks. Instructors are encouraged to include personal examples when presenting the material but to stay consistent with the core of the material. In addition, during the two-year implementation of this course, of five adjunct faculty who taught the course with the old curriculum, only 2 were teaching when the survey was conducted. Thus, the variability in instructor ability was reduced through attrition and careful hiring of new instructors.

Interestingly, neither class status (i.e., freshman, etc.) nor class time (i.e., morning, afternoon, etc.) had any significant bearing on the students' assessment of the simulation exercise.

Instructor quality did surface in a rudimentary review of the students' open-ended responses to the following questions: "What was the best thing about this course?" "How would you improve this course?," "What did you like about the style/manner in which I taught? i.e. what did I do well?" "What did you dislike about the style/manner in which I taught? i.e. what could I improve?" "Please feel free to provide additional comments about the course or instructor." In a review of the first 100 open ended responses, 40% of students reported that ScrimmageSIM was the best part of the course. Students reported varying degrees of satisfaction with the quality of instructor, specifically as it pertained to instructor's knowledge of the simulation and ability to answer questions. It became clear in reviewing the qualitative data that the instructor's role in student success in this particular class is important. For example, students either reported comments akin to *"Instructor was great and made the course more interesting"* or more negative comments like *"If I had to take it [this course] again, I would take it with another professor."*

5. DISCUSSION AND CONCLUSION

There is currently little consistency in college-level introduction to business courses. The change in WMU's required general education courses provided an opportunity to review the purpose of the introduction to business course at WMU. The new course is designed to prepare business students for their future studies by providing an experiential learning environment where they can appreciate the importance of financial information and quantitative models. For non-business students, the class provides a strong foundation in how business operate and the need to integrate different business functions.

This course redesign has shown that, with the proper design and student support resources, students can succeed in a quantitatively challenging course.

The new course has also been challenging for some instructors. One adjunct instructor opted out of teaching the course before it's initial offering, two opted out after the first year and one was not renewed after the second year. With some effort, new instructors have been found that are up to the challenges of the new curriculum, which requires instructors to learn to operate the simulation, refresh their knowledge of accounting fundamentals, and learn how to integrate the simulation experience into the regular classroom sessions.

Faculty who are interested in implementing this curriculum in their introduction to business course can contact the lead author to get access to all of the teaching and support materials, including lecture PowerPoint files, exam test banks, assignments, etc.

Future research is being planned to determine if the revised introduction to business course is contributing to better performance of business students in later business courses like accounting.

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Editor's Note:

This paper was selected for inclusion in the journal as the 2023 ISCAP Conference Best Data Analytics Paper The acceptance rate is typically 2% 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 2023.

APPENDIX A
Comparison of Introduction to Business Courses at 17 Top-Ranked Schools

School	Year Offered / Credit Hours / Required	Professional Communications	Professional Development	Survey of Business Disciplines	Course Projects (Team vs. Individual)
Bentley	Fr / 1 / yes	NA	Yes	No	Individual
Boston College	Fr / 3 / yes	Yes	Yes	Yes	Both
Cornell	Fr / 4 / yes	Yes	Yes	Yes	Both
Georgetown	Fr / 3/ no	NA	NA	Yes	Team Case Competition
Indiana	Fr / 1.5 / yes	NA	Yes	Yes	Individual
Michigan	Fr / 1 / yes* Fr / 0 / yes	NA NA	Yes Yes	Yes Yes	NA NA
NYU	Fr / 0 / yes	Yes	Yes	Yes	Team
Northeastern	Fr / 4/ yes* Fr / 0 / yes	Yes NA	No Yes	Yes NA	Team
Ohio State	So / 3 / yes	Yes	Yes	Yes	Team
Penn State	Fr / 1 / yes	Yes	Yes	Yes	Both
Syracuse	Fr / 3/ yes	YES	NA	Yes	Team
Penn	Fr / 0.5 / yes pass/fail	NA	Yes	Yes	Individual
Texas	Fr / 1/ yes	Yes	Yes	No	Individual
Villanova	Fr / 3 / yes	Yes	Yes	Yes	Both
Wake Forest	Fr / 3 / yes	NA	NA	Yes	NA
Washington U.	Fr / 3 / yes Fr / 2 / yes	NA Yes	NA Yes	Yes NA	NA Team
William & Mary	Jr / 1 / yes pass/fail	Yes	Yes	Yes	Both

Fr - Fresman Year, So - Sophomore Year, Jr - Junior Year, Sr - Senior Year
* Two-course sequence required for most students.

APPENDIX B
Comparison of WMU General Education Curriculum with the new Essential Studies Curriculum

General Education Curriculum

Proficiency Courses
- College-level writing course
- Baccalaureate-level writing or writing-intensive course
- College-level mathematics or quantitative reasoning course

Distribution Areas
- Area I – Fine Arts
- Area II – Humanities
- Area III – The United States: Cultures and Issues
- Area IV – Other Cultures and Civilizations
- Area V – Social and Behavioral Sciences
- Area VI – Natural Sciences with Laboratory
- Area VII – Natural Science and Technology: Applications and Implications
- Area VIII – Health and Well-Being

Essential Studies Curriculum

Level 1 – Foundations
- Writing
- Oral and Digital Communications
- Quantitative Literacy
- Inquiry and Engagement

Level 2 – Exploration and Discover
- Personal Wellness
- World Language and Culture
- Artistic Theory and Practice
- Scientific Literacy with a Lab
- Science and Technology
- Societies and Cultures

Level 3 - Connections
- Local and National Perspectives
- Global Perspectives

APPENDIX C
Table of Contents for Pearson Publishing Introduction to Business Textbooks

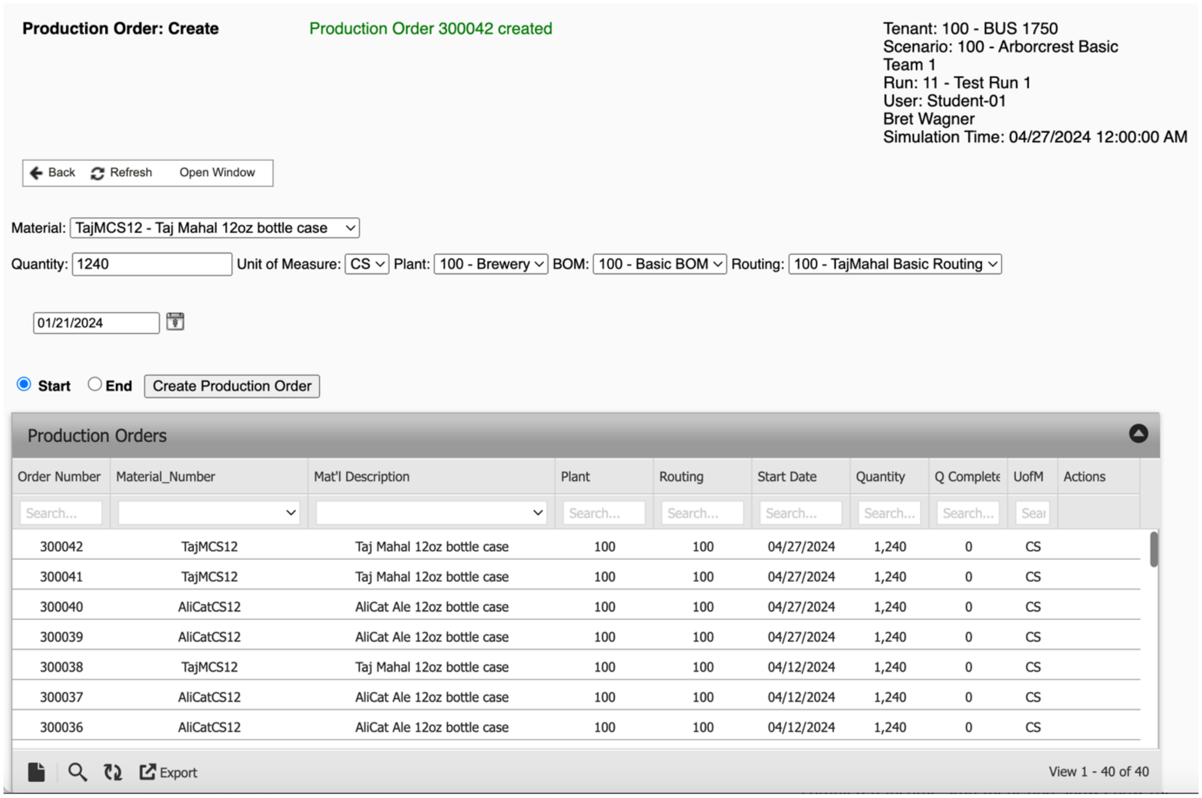
Title	**Better Business**		**Business Essentials**	**Business in Action**
Authors	**Solomon, Poatsy & Marin**		**Ebert & Griffin**	**Bovee & Thill**
Publisher	**Pearson**		**Pearson**	**Pearson**
Chapters				
1	Business Basics		The US Business Environment	Developing a Business Mindset
2	Economics		Understanding Business Ethics and Social Responsibility	Economics, Money and Banking
3	Ethics in Business		Entrepreneurship, New Ventures, and Business Ownership	The Global Marketplace
4	Business in a Global Economy		Understanding the Global Context of Business	Business Ethics and Corporate Social Responsibility
5	Business Law (mini chapter)		Managing the Business	Forms of Ownership
6	Small Business and Entrepreneurship		Organizing the Business	Entrepreneurship and Small-Business Ownership
7	Forms of Business Ownership		Operations Management and Quality	Management Roles, Functions, and Skills
8	Constructing an Effective Business Plan (mini chapter)		Employee Behavior and Motivation	Organization and Teamwork
9	Business Management and Organization		Leadership and Decision Making	Production Systems
10	Motivation, Leadership, and Teamwork		Human Resource Management and Labor Relations	Employee Motivation
11	Human Resources		Marketing Processes and Consumer Behavior	Human Resource Management
12	Online Business and Technology		Developing and Pricing Products	The Art and Science of Marketing
13	Production, Operations, and Supply Chain Management		Distributing and Promoting Products	Product Management and Pricing Strategies
14	Business Communications (mini chapter)		Information Technology (IT) for Business	Customer Communication and Product Distribution
15	Marketing and Consumer Behavior		The Role of Accountants and Accounting Information	Financial Information and Accounting Concepts
16	Product Development, Branding, and Pricing Strategies		Understanding Money and the Role of Banking	Financial Management and Financial Markets
17	Promotion and Distribution		Managing Business Finances	
18	Finding a Job (mini chapter)	Appendices	Risk Management	
19	Finance and Accounting for Business Operations		The Legal Context of Business	
20	Investment Opportunities in the Securities Market		Managing your Personal Finances	
21	Personal Finance (mini chapter)		Unions and Labor Management	
22				
23				
24				

APPENDIX D
Table of Contents for McGraw-Hill Introduction to Business Textbooks

Title	**Business Foundations**		**Understanding Business**
Authors	**Ferrell, Hirt & Ferrell**		**Nickels, McHugh & McHugh**
Publisher	**McGraw-Hill**		**McGraw-Hill**
Chapters			
1	The Dynamics of Business and Economoics		Taking Risks and Making Profits within the Dynamic Business Environment
2	Business Ethics and Social Responsibility		Understanding Economics and How It Affects Business
3	Business in a Boarderless World		Doing Business in Global Markets
4	Options for Organizing Business		Demanding Ethical and Socially Responsible Behavior
5	Small Business, Entrepreneurship, and Franchising		How to Form a Business
6	The Nature of Management		Entrepreneurship and Starting a Small Business
7	Organization, Teamwork, and Communication		Management and Leadership
8	Managing Operations and Supply Chain		Structuring Organizations for Today's Challenges
9	Motivating the Work Force		Production and Operations Management
10	Managing Human Resources		Motivating Employees
11	Customer-Driven Marketing		Human Resource Management: Finding and Keeping the Best Employees
12	Dimensions of Marketing Strategy		Dealing with Employee-Management Issues
13	Digital Marketing and Social Media		Marketing: Helping Busyers Buy
14	Accounting and Financial Statements		Developing and Pricing Goods and Services
15	Money and the Financial System		Distributing Products
16	Financial Management and Securities		Using Effective Promotions
17			Understanding Accounting and Financial Information
18			Financial Management
19			Using Securities Markets for Financing and Investing Opportunities
20			Money, Financial Institutions, and the Federal Reserve
21		Bonus	Working within the Legal Environment
22		Bonus	Using Technology to Manage Information
23		Bonus	Managing Risk
24		Bonus	Managing Personal Finance & Investing

APPENDIX E
Key Screens in the ScrimmageSIM Simulation

Production Order Screen



Production Order: Create

Production Order 300042 created

Tenant: 100 - BUS 1750
Scenario: 100 - Arborcrest Basic
Team 1
Run: 11 - Test Run 1
User: Student-01
Bret Wagner
Simulation Time: 04/27/2024 12:00:00 AM

Back | Refresh | Open Window

Material: TajMCS12 - Taj Mahal 12oz bottle case

Quantity: 1240 Unit of Measure: CS Plant: 100 - Brewery BOM: 100 - Basic BOM Routing: 100 - TajMahal Basic Routing

01/21/2024

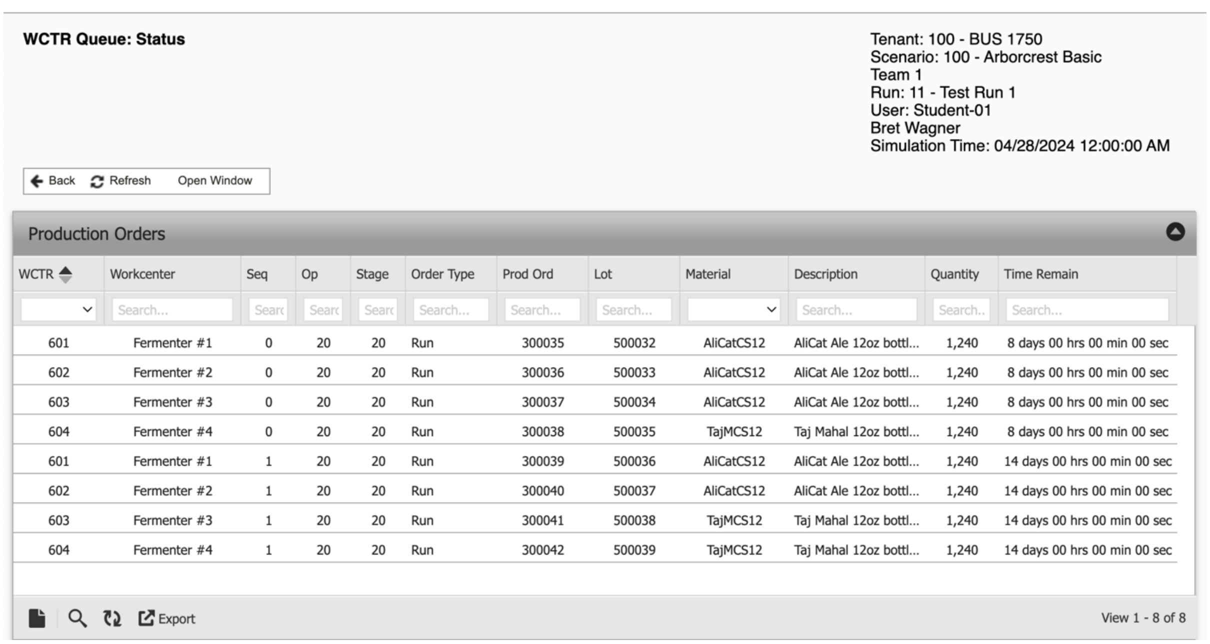
Start End Create Production Order

Production Orders

Order Number	Material_Number	Mat'l Description	Plant	Routing	Start Date	Quantity	Q Complete	UofM	Actions
300042	TajMCS12	Taj Mahal 12oz bottle case	100	100	04/27/2024	1,240	0	CS	
300041	TajMCS12	Taj Mahal 12oz bottle case	100	100	04/27/2024	1,240	0	CS	
300040	AliCatCS12	AliCat Ale 12oz bottle case	100	100	04/27/2024	1,240	0	CS	
300039	AliCatCS12	AliCat Ale 12oz bottle case	100	100	04/27/2024	1,240	0	CS	
300038	TajMCS12	Taj Mahal 12oz bottle case	100	100	04/12/2024	1,240	0	CS	
300037	AliCatCS12	AliCat Ale 12oz bottle case	100	100	04/12/2024	1,240	0	CS	
300036	AliCatCS12	AliCat Ale 12oz bottle case	100	100	04/12/2024	1,240	0	CS	

Export View 1 - 40 of 40

Workcenter Queue Screen



WCTR Queue: Status

Tenant: 100 - BUS 1750
Scenario: 100 - Arborcrest Basic
Team 1
Run: 11 - Test Run 1
User: Student-01
Bret Wagner
Simulation Time: 04/28/2024 12:00:00 AM

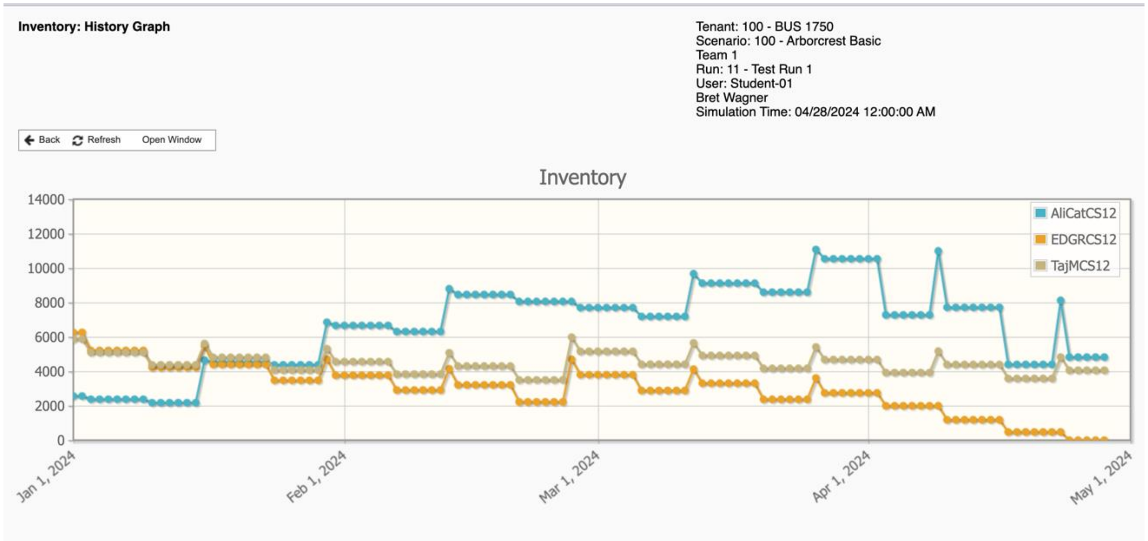
Back | Refresh | Open Window

Production Orders

WCTR	Workcenter	Seq	Op	Stage	Order Type	Prod Ord	Lot	Material	Description	Quantity	Time Remain
601	Fermenter #1	0	20	20	Run	300035	500032	AliCatCS12	AliCat Ale 12oz bottl...	1,240	8 days 00 hrs 00 min 00 sec
602	Fermenter #2	0	20	20	Run	300036	500033	AliCatCS12	AliCat Ale 12oz bottl...	1,240	8 days 00 hrs 00 min 00 sec
603	Fermenter #3	0	20	20	Run	300037	500034	AliCatCS12	AliCat Ale 12oz bottl...	1,240	8 days 00 hrs 00 min 00 sec
604	Fermenter #4	0	20	20	Run	300038	500035	TajMCS12	Taj Mahal 12oz bottl...	1,240	8 days 00 hrs 00 min 00 sec
601	Fermenter #1	1	20	20	Run	300039	500036	AliCatCS12	AliCat Ale 12oz bottl...	1,240	14 days 00 hrs 00 min 00 sec
602	Fermenter #2	1	20	20	Run	300040	500037	AliCatCS12	AliCat Ale 12oz bottl...	1,240	14 days 00 hrs 00 min 00 sec
603	Fermenter #3	1	20	20	Run	300041	500038	TajMCS12	Taj Mahal 12oz bottl...	1,240	14 days 00 hrs 00 min 00 sec
604	Fermenter #4	1	20	20	Run	300042	500039	TajMCS12	Taj Mahal 12oz bottl...	1,240	14 days 00 hrs 00 min 00 sec

Export View 1 - 8 of 8

Inventory History Graph Screen



Financial Statement Screen

Financial Statements

Tenant: 100 - BUS 1750
Scenario: 100 - Arborcrest Basic
Team 1
Run: 11 - Test Run 1
User: Student-01
Bret Wagner
Simulation Time: 04/28/2024 12:00:00 AM

Back Refresh Open Window

Name	Acct/Cat	Current	Dr./Cr.
Financial Statements	-	-	-
Income Statement	-	54,434	-
Gross Profit	1010	264,078	-
Sales Revenue	400000	716,118	Cr.
Cost of Goods Sold	500000	452,040	Dr.
Expenses	1020	209,644	-
Conversion Cost	600000	952	Dr.
Advertising Promotion and Selling	600100	35,377	Dr.
General & Administrative	600200	76,738	Dr.
Depreciation Machinery Plant & Equipment	600300	6,333	Dr.
Depreciation Buildings and Improvements	600400	10,833	Dr.
Salary & Wage Expense	600500	57,639	Dr.
Interest Expense	600600	22,048	Dr.
Conversion Variance	900100	-276	Dr.
Material Variance	900200	0	Dr.
Balance Sheet	-	0	-
Assets	2010	3,755,954	-
Liabilities	2020	1,582,751	-
Owner's Equity	2030	2,173,203	-

APPENDIX F
ScrimmageSIM Experiential Learning Spiral

Concrete Experience	Reflective Observation	Abstract Conceptualization	Active Experimentation
Scenario 100, Run 1 1. Schedule Production	1. Revise paper 2. Review data 3. Rerun scenario 4. Absorption Costing	1. Planning Spreadsheet 2. Planning vs. Execution	1. Planning Spreadsheet 2. Team Planning Meeting
Scenario 100, Run 2 1. Schedule Production	1. Review data 2. Rerun scenario 3. Gross Margin, Operating Margin 4. Elasticity, Price Changes & Capacity Constrains	1. Planning Spreadsheet with Pricing	1. Planning Spreadsheet 2. Team Planning Meeting
Scenario 200 1. Schedule Production 2. Change Prices	1. Review data 2. Rerun scenario 3. Capacity Expansion 4. Loans & Compound Interest	1. Planning Spreadsheet with Pricing & Capacity Expansion	1. Planning Spreadsheet 2. Team Planning Meeting
Scenario 220 1. Schedule Production 2. Change Prices 3. Expand Capacity 4. Pay off loans	1. Review data 2. Rerun scenario 3. New Product Introduction 4. Standard Costs **5. Scenario 220 Presentation**	1. Planning Spreadsheet with Pricing, Capacity Expansion & New Product	1. Planning Spreadsheet 2. Team Planning Meeting
Scenario 230 1. Schedule Production 2. Change Prices 3. Expand Capacity 4. Pay off loans 5. Produce 4th product	1. Review data 2. Rerun scenario		

The Perceptions of Undergraduate Students Associated with a Career in Technology – An Analysis by Academic Year

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Abstract

In both the educational and business environments, two trends may be inarguable. The difference between the demand of technology positions as compared to the number of people majoring or interested in technology-based careers. Secondly, the education environment is radically changing in several aspects including a high number of undecided majors entering undergraduate institutions as well as the ability of skills development by higher education students entering the marketplace. The recent and historic attention in artificial intelligence and machine learning technology may have an impact on both a change in the demand for total positions and interest in technology-based careers. This research study will investigate the attitudes and perceptions of first-year college students over four academic years to determine changes. Six of the factors studied were found to have significant differences between the research period: attitude, job availability, personal image, social image, subjective norm and intent to major. The intent to major has remained consistently low for three of the four years. The implications from this research will provide insight to both business organizations for recruiting as well as all educational institutions.

Keywords: Technology career, Student perceptions, Career exploration, Experiential integration

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The Perceptions of Undergraduate Students Associated with a Career in Technology – An Analysis by Academic Year

Kenneth J. Sousa

1. INTRODUCTION

Demands of Business Organizations
Since the early 1980s, information technology has become a dominant influence for business organization in both strategic, business analysis and operational activities. The rising dependence and integration of technology systems requires a corresponding need for technology personnel. Technology personnel will require skills and conceptual knowledge. The source of these requirements can be gained from either traditional higher education undergraduate colleges (two- and four-year) as well as technical institutions. However, the demand for personnel compared to people completing a technology-based major is widely different.

Technology Career Trend and Supply
The lack of role models is one of the most significant challenges for women in technology careers. Women hold less than 20% of all technology leadership positions (Clay, 2023). A recent survey found that 84% of the respondents believed that the chief information officer (CIO) has a critical influence to lead business and technology transformation (Drinkwater, 2022). This fact asserts that the information technology function and responsibilities have evolved from operation-focused activities (processing and reporting data) to business analysis/strategy (mobile applications, data analytics). Therefore, the integration of technology outcomes requires the availability of skilled talent.

Another critical component of this discussion is associated with the gender gap. Christensen and Knezek (Christensen & Knezek, 2017) found that middle school males generally have higher intent to pursue a career in STEM. Females are underrepresented in technology-based positions. Currently, women hold only 26% of the technology related positions (Hubbert, 2023). The percentage of females in technology firms (> 10K employees) is the same. Additionally, the percentage of work in technology positions has decreased by 2.1% over the last two years. One of the issues that may affect the low employment of young women is the lack of role models associated with CEO and leadership roles as well as imposter syndrome tendencies (Clay, 2023; Hubbert, 2023). Imposter syndrome is a consistent disbelief that one's success is deserved or legitimately achieved as a result of an individual's effort and/or skills.

Research Objective
The objective of this study is to examine the attitudes and perceptions of first-year undergraduate college students specific to technology careers and majors to explore trends, if any, over a five-year period. The response data will be categorized into four groups to examine the data as shown below in Table 1. These groups are comprised of data collected for two semesters (fall and spring).

Group	Academic Year
1	2016-17
2	2017-18
3	2020-21
4	2021-22

Table 1 – Survey Groups

These academic years were chosen because a full academic year which included a survey administration including two semesters (both Fall and Spring), rather than only one semester in an academic year.

The results of this study found that six of the twelve factors resulted in significant differences between the means for the four groups shown above. The results associated with attitude, job availability, personal image, social image, subjective norm and intent to major. Four of the factors (personal image, social image, attitude, and job availability), increased from the base year (2016-17 to 2021-22) with differences between 0.21 – 0.48. The remaining two factors (intent to major and subjective norm) resulted in minimal change (-0.07 – 0.01).

2. LITERATURE REVIEW

Employment Data for Technology Careers
From an anecdotal perspective, it is common knowledge that demand for technology professionals continues to increase over the next decade. The U.S. Bureau of Labor Statistics compiles data associated with occupations are compiled in Table 1.7. A summary of the various

occupational codes associated with technology careers, under the Computer and Mathematical Occupations summary (BLS employment matrix code: 15-0000) has been compiled into Table 2 (U.S. Bureau of Labor Statistics, 2023).

The first row depicts the summary statistics for the 15-0000 matrix code. The remaining rows of Table 2 summarize all matrix codes relating to the six computer (technology) occupations summarized within the 15-xxxx matrix code. The last row provides a total of the computer occupation sub-codes (six). The projected growth for all computer operations matrix codes over a ten-year period through 2032 is 14.2%. However, several sub-classifications (analysts, scientists, support specialists) are double-digit growth (14.9%, 22.7% and 21.7%).

Comparing BLS data from two time periods (2022 and 2032), the occupations with the largest estimated increase are Software and Web Developers (51%) and Computer and Information Analysts (19%). Two occupations have negative trends (Computer Support Specialists and Database and Network Administrators).

Table 2 – Trends in Information Technology Careers (BLS Table 1.7)

While government statistics are important, empirical data relating to actual open job positions can provide more clarity. An analysis of the technology position openings was compiled every six months from August 2021 through August 2022 from a large financial services firm. The open job statistics for technology positions have tracked at 389 (August 2021), 549 (February 2022) and 546 (August 2022). The larger number of positions during 2022 may have resulted due to pandemic and early retirement decisions. While the number of open positions is decreasing, the current number of positions at 271 (September 2023) continues to illustrate a high number of open positions. In addition, it is consistent with the BLS annual average openings. For example, BLS projects the need for 179 thousand positions for software and web developers through 2032.

Factors Influencing Student Perceptions

A compilation of foundational research is required to form the basis of the factors to investigate the perceptions of students toward a technology career. These factors would form the definition of a model to support the objective of this research. Various research studies were examined and reviewed to gather the appropriate factors for the research model. A review of literature was compiled to identify research studies which focused on a range of factors to collect data associated with the attitudes toward career choices with a STEM or technology focus.

Moore & Burrus (2019) applied the Theory of Planned Behavior from Ajzen (1991) to include several factors including subjective norms, perceived behavioral control and intention to major. Finlay et al (1999) defined subjective norm as an individual's opinion or perception about what others believe the individual should do. Ultimately, influence integrates an individual's peers, family, and friends. Several research studies identified parents (and their professions) as an influence on their child's career (Cohen & Hanno, 1993; Law & Yuen, 2012; Pearson & Dellman-Jenkins, 1997; Saleem et al., 2014). Kuechler et al. (2009) found that both families and advisors significantly affected the intention to choose an IS major. Subjective norms and attitudes were also found to predict intentions (Hagger et al., 2015).

Information and data can be gathered from many sources including informal (word of mouth) and formal (structured and codified sources). Walstrom et al. (2008) researched the various information sources associated with information systems careers. Based on the average importance (six-point scale) from student responses, the top four sources (average scores > 3.0) were information from college/department websites, brochures about the major, information on the web/internet, and newspaper articles (Walstrom et al., 2008). The most influential information is from the institution's internal sources.

The research by Wu et al. (2018) investigated various factors in relation to STEM careers to include their attitudes, beliefs, confidence, and enjoyment. Experiential attitude is defined as whether an object or behavior is considered pleasant or enjoyable while instrumental believes that the object or behavior is useful and worthwhile. Moore and Burrus (2019) investigated two dimensions of attitudes; experiential and instrumental. Moore and Burrus believed that experiential attitudes that consider math boring by students may affect their attitudes toward STEM-related activities. Additionally, a student's instrumental attitude toward math may not be considered important for their future career decisions. Therefore, these attitudes will reduce their engagement toward math courses and careers.

Kuechler (2009) found that a genuine interest in IS as significant factor to intent to major. Walstrom et al. (2008) found that 56% of the respondents said that information systems was not of interest to them. Additionally, Walstrom found the highest factor in the choice of major was personal interest in the subject matter (5.1 / 6). Compeau & Higgins (1995) found that IS majors are collectively motivated by self-efficacy, work value congruency and normative beliefs. Work value and normative beliefs relate the factors of work environment and subjective norm respectively.

Decisions are often completed based on outcome expectations. The declaration of an undergraduate major is a natural and required decision for a college student. Bandura (1986) believed that these outcomes are based on an integration of the results of actions. Bandura's research categorized these outcomes in three categories: physical, social, and self-evaluating. Three factors from Bandura have been integrated into this study including job availability, job salary, and work environment. Additionally, Bandura believed that the reaction of others (family and friends) as well as the social impact of the environment lead to several factors to be explored by this study (social image, personal image). The starting salary and availability of jobs factor were supported as important factors (4.8/6.0) as reported by students (Walstrom et al., 2008).

Heinze & Hu (2009) found that undergraduate students who had a positive attitude toward IT careers and higher perceived behavioral control regarding IT majors had a greater intention to major in IT. Their research measured the control beliefs of students that will affect the pursuit of an IT major using the definition of CSE.

The image, both personal and social, could provide an influence on the selection of an IT Major. The personal image is reflective of the students' self-image of technology professionals while the social image is focused on whether it is a respectable career. Kuechler (2009) found a positive effect on intent to major from social image while no significance on personal image (PI). Walton (2012) researched the power of social connections enhanced achievement motivation.

After reviewing the various research studies, twelve factors were found to be appropriate measures of student perceptions relating to adoption of technology majors and careers. These studies were used to compile a list of questions to form a survey instrument to gather data to support the research objective. Each of these factors is described in Table 3 with a full listing of the survey questions in Table 9.

Table 3 – Citations for Research Model Factors

Research Hypotheses

Based on the research objective and the completion of the literature review, twelve hypotheses have been developed to complete the research model. Table 4 defines a detailed listing of the research hypotheses.

Table 4 – Summary of Research Hypotheses

3. RESEARCH METHODOLOGY

Survey Instrument

To complete the research objective, a survey instrument was designed to include questions to gather data on students' perceptions. The final survey instrument included 36 questions to gather the perceptions and beliefs for the factors outlined in Table 4. Many of the questions were gathered from either research included in Table 4 as well as other articles used in the literature review. In a few cases (e.g., media influence), the questions were structured based on the media categories included from past research studies.

These questions were structured using a Likert scale for the student's response. A seven-point scale was selected in order to show higher reliability than any number of options (Chang, 1994; Wakita et al., 2012). The seven-point scale also includes a benign response in the middle of the scale (neither agree or disagree). Two Likert scale structures were used for each of the questions: 1) strongly disagree vs. strongly agree and 2) not important vs. extremely important. The values associated were designed from 7 (strongly agree, extremely important) to 1 (not important, strongly disagree). Table 5 outlines the details of the survey instrument.

Table 5 – Summary of Survey Composition by Factor

Several questions were included for classification purposes including gender, grade point average, and the completion date (semester) of the survey.

Survey Sample and Administration

The population selected for this study consisted of first year students. Since most courses completed in the first year consist of core/general education courses, this population was selected to gain perceptions early in their higher education experience. Students entering higher education as undecided are considered high-risk while a significant percent (61%) change their major (Mowreader, 2023). A study completed by Junior Achievement USA found that only 46% of students believed that they should have a concrete career goal after starting college but before graduating (Anonymous, 2019). All responses associated with this research are from one higher-education institution, a four-year university.

An electronic survey software tool (Qualtrix) was used at the portal for the administration of the survey. The individual questions associated with the factors were scattered throughout the survey to increase reliability of responses. All questions were set up with a required response to each survey question except for the gender question. In the initial deployment of the survey, the gender question inadvertently was not set up properly allowing no response to the question. Therefore, the early semesters contained some "empty" responses for the gender question.

4. FINDINGS AND RESULTS

Population Assumptions

All surveys were administered in a business course required of all first year and transfer students. Students cannot complete multiple surveys within the same semester while registered for different courses. Therefore, the independence of observations as well as the homogeneity of variance assumptions associated with the survey population are appropriate and valid.

Survey Response

For this research study, the survey data was confined to four years (eight semesters) as shown in Table 6 below.

Table 6 – Frequency of Survey Results

The composition of males and females (57.3% and 31.9%) are like the distribution of students at the university. As noted previously, the initial version of the survey did not require the entry of a response to the gender question. Since this research does not investigate any differences with gender, all respondents (1,128) were included in the analysis.

ANOVA Results

Twelve summary variables were created for each of the factors. The average of the individual questions associated with each factor (as outlined in Table 5) was calculated for each factor. The SPSS Mean function was used to calculate the mean of the individual question responses to exclude missing values (no response to a question).

An analysis of variance (ANOVA) was completed on the survey response data using the average (mean) of the twelve factors. The statistical results of the ANOVA mean values have been compiled in Table 7. The table includes the four group means (academic years) as well as the grand mean for the twelve factors. It also includes the number of observations (n) for each factor.

Table 7 – Summary of Group and Grand Means by Factor

The results of the ANOVA statistical test of significance values (p-value) associated with each of the twelve factors. The following table (Table 8) summarizes the values of the ANOVA.

Table 8 – Summary of ANOVA Test of Significance Results

Hypotheses Evaluation

Of the twelve factors analyzed, only six factors have resulted in significant differences between the mean values: Attitude, Job Availability, Personal Image, Social Image, Subjective Norm, and Intent to Major. Three of these factors calculated a highly significant p-value ($p<.001$). The remaining six factors (Aptitude, Difficulty of Major, Interest in IT, Job Salary, Media Influence, and Workload Environment) resulted in no significant differences between the mean values of the four academic years.

Each of the twelve hypotheses were evaluated based on the results of the ANOVA tests as shown in the previous table. A summary of the evaluation of the null hypotheses is contained in Table 9.

The ANOVA calculated 48 calculated group means (four years multiplied by 12 factors). Most of the differences between group means and the factor grand means were less than 0.10. As expected, each one of the factors resulting in significant differences included at least two mean differences (group mean – grand mean) greater than 0.09. Two of the factor's grand mean with $p<.05$ were greater than 5; personal image (5.56) and social image (5.30).

Hypothesis	Result
H1	Accept
H2	***Reject***
H3	Accept
H4	Accept
H5	***Reject***
H6	Accept
H7	Accept
H8	***Reject***
H9	***Reject***
H10	***Reject***
H11	Accept
H12	***Reject***

Table 9 – Summary of Research Hypotheses

5. DISCUSSION AND IMPLICATIONS

Discussion

Six of the ANOVA tests (50%) resulted in significant differences between the four academic years. Students' perceptions have not changed in the areas of aptitude, difficulty of the major, interest in technology, job salary, media influence, and workload environment. The lack of change for some factors is not surprising, specifically with aptitude and difficulty of major; with the associated group means (3.17 – 3.53) below the benign response value of four. Anecdotally, many students believe that science- and mathematical-based majors are more difficult and require a higher aptitude for success. Technology-based careers often follow a similar stereotype as mathematics and science careers.

The group mean values associated with the media influence were less than 4.36 (equating just higher than neither agree/disagree response). With the exponential increase in the use of social media, the influence of media on younger age groups has changed significantly since this study began in 2016. The author considered changing the various categories of media at various points over the last few years. However, it would have precluded any multi-year, such as this research study, analysis as the scale would have changed. The workplace environment issue is also not surprising. With the group means between 4.82 and 4.97, their responses are just below a *slightly agree* response. After reviewing the question averages in detail, students believe that the environment for technology professions lacks four traits: 1) no variety in tasks, 2) fails to lead to leadership positions, 3) lack of creativity, and 4) will not benefit people and society.

The two remaining nonsignificant factors (interest in technology and job salary) are more puzzling. The group mean values remained close to the *slightly agree* response (5). The interest in information technology careers investigates five perceptions (learning software, working in a team, using software, and analyzing/presenting business-related problems). Considering the level of technology adoption associated with young people, the results of this survey can only provide one conclusion – students enjoy using technology, but not as a career. Students enjoy using their phone or tablet. However, they do not have any interest in developing mobile or desktop applications. The author believes that technology has become an "appliance" like a refrigerator or a car. They know that the equipment works when the power is turned on, but do not care how it works. It simply functions for the purpose in which students desire.

The group mean scores for the job salary factor resulted between 4.73 and 4.94; again, below the *slightly agree* response. With the current level of information about job postings available online, it is surprising that students are not more knowledgeable about the higher salaries for technology personnel.

Six of the factors resulted in significant differences between the means of the four academic years (attitude, job availability, personal image, social image, subjective norms, and intent to major). The group mean scores for attitude and job availability are like the responses of previous factors reflecting a *slightly agree* response (5) to the questions. The image factors (personal and social image) calculated group means between 5.16 and 5.92. These values are trending closer to the *agree* response (6) suggesting a more positive image toward technology personnel and careers. On a positive note, these factors (attitude, personal image, and social image) have all realized significant increases over the last two academic years (0.42, 0.44, 0.39 respectively).

The subjective norms and intent to major factors ($p<.05$) are concerning and require some discussion. These factors calculated mean values which are the lowest of the twelve factors. The grand means for subjective norms and intent to major are 2.92 and 2.51 respectively; below the *slightly disagree* response for the questions. These results illustrate that students have limited interest in majoring in technology. Additionally, the results of the subjective norm factor indicate that the advice of several groups (family, friends, advisors, peers, and educators) suggest that information technology careers are not a "*good fit*" for them. It is plausible that these subjective norms may influence, possibly negatively, the major decision.

The importance of the results could be interpreted in a variety of ways using the base (2016-2017) and final year (2021-22) of the study as well as the four years of individual means.

Of the six factors identified as statistically significant, the only factor (subjective norm) declined from the base year to the last year; a small decline of 2.4%. The subjective norm for AY2017-18 to AY2020-21 years declined by 12.1%; (3.06 to 2.69); while increasing slightly to 2.84 in AY2021-22. These results can explain that the pandemic shutdown in early-2020 affected education and its students at all levels with the importance of relationships.

These results could be explained by avoidant coping. Madrigal and Blevins (2022) believed that students escaped the challenges and or stressors caused during the pandemic. Self-medicating the lock-down period with social media breaks. Madrigal and Blevins reported that students' sources of support decreased during the pandemic from the pre-pandemic period. Therefore, it is conceivable that this period reduced the consistency, frequency, and depth of relationships with the groups associated with the subjective norms. Furthermore, Madrigal reported that while there was decrease in socialization with many groups, social media/technology use increased during the same period. Other research supports the loss of social support, isolation, development of social relationships and interaction (Alsubaie, 2022; Elmer et al., 2020; Luan et al., 2023). While these discussions are all negative, there should be some hope that the post-pandemic period will rebuild and restore the interaction in an education setting as noted in the small rise in subjective norm for the last study year.

Personal image factor was the only factor to have increased steadily over the four-year study period. It is plausible that the increase of students' personal image of technology may been explained by the increase in the of technology in classes as well as the new teleconferencing software deployed during the lockdown. The increased reliance during these periods may have acclimated students with technology throughout their educational journey. Additional exposure can create knowledge and a level of comfort in any subject.

The remaining factors (attitude, job availability, social image, and intent to major) resulted in various increases and decreases over the four research years. Except for intent to major factor, the last research year (2021-22) all resulted in an increase over the grand mean for each period. Considering all the turbulence and challenges, over the six years of the research period, this may provide some positive influence on the future academic years.

Practical Implications and Conclusions

If the research period is an accurate representation of undergraduate students' perceptions, the intent to major shows challenging "headwinds" toward the future. In three of the four research years, students clearly responded closer to the "disagree" response (2.0) to the question that they intend to major in information technology.

The results of this research clearly indicate that the population does not consider technology a suitable career. Therefore, if these perceptions are believed to be accurate on a broader scale, the gap between the demand and supply of candidates for technology positions in the marketplace will continue to be wider. The consequences for business organizations will consist of delayed project delivery, reduction in completed projects, increased salaries to retain/attract personnel, and/or increased offshoring deployment of technology activities.

The current trend of technology appears to imitate the issues associated with the accounting profession. The accounting industry is experiencing a sharp decline in the number of accounting majors while the 300,000 accountants/auditors have left their positions in the last two years (Ellis, 2022; Somaiya, 2023). A study by Hsiao (2016) researched factors to investigate career choices in accounting including intrinsic characteristics (contribution to society, challenge, workplace environment), extrinsic characteristics (job availability/salary), and influence on decisions (subjective norms).

Students sometimes have incomplete and inaccurate stereotypes of technology-based careers. One of these stereotypes focuses on the advancement to a leadership position. The chief-information officer (CIO), has transitioned from the "back-office manager and order taker" to an organizational leader managing the strategic decisions which require technology integration (Stackpole & Betts, 2011). Stackpole asserts that 84% of CIOs are viewed as a "critical changemaker" accepting the leadership of business and technology.

A recent article highlighted a list of the highest paying technology positions (Anonymous, 2023). Three of those job titles would be considered "steppingstones" positions from entry-level to leadership (CIO-type) positions: project manager, program analyst/manger, and MIS manager. These job titles earn an average salary of $130k with a salary increase of 13.1% over the last two years.

Implementation Strategies
Higher education institutions should create educational outreach programs to be successful (Rajala et al., 2023). Five implementation strategies have been compiled to address the conclusions and implications of this research.

Promotion of Career – Many students major in marketing to be employed in entry-level positions as sales representatives gaining experience and knowledge about their trade (sales techniques, communication, proposals, etc.) to build a collection of skills to transition to leadership positions (sales managers, strategy analysts, sales vice presidents). Promotional and educational materials should include detailed narratives and examples focusing students' attention on the transition from entry-level positions through middle-management and then to leadership positions. Technology positions should be no different. Specific narratives with applied examples (professional profiles of people from industry, job postings, etc.) will engage students with facts to negate speculation or stereotypes.

Exposure to Technology Careers and Personnel – It is important to create a "*vision*" of various technology careers and occupations. A recent study found that participants in outreach programs for IS did not receive any information about IS, ICT or any computing-related field (Rajala et al., 2023). While this study was compiled in Finland, a similar experience may be formed in U.S. secondary schools. Therefore, it would be important to expose students to the actual tasks and responsibilities of some technology occupations. In addition, this exposure is required to refute the "Wargames" (the movie) stereotype in which students believe that technology positions are "chained" to their desk developing code, hacking, and monitoring computer systems.

Many positions, specifically computer and information analysts (15-1210), are responsible for analyzing and documenting processes, integrating corporate strategies, innovative technology requirements and solving business problems through technology. However, these positions do <u>not</u> require or consist of coding and advanced technical skills. Additionally, many information technology personnel are promoted as Project Mangers. These positions require presentations, project management, analysis, and meeting with various stakeholders of a business. Again, all non-technical and business-oriented tasks performed by technology-based occupations.

Research supports that the level of self-efficacy associated with career decisions is a significant predictor of occupational indecision and career exploration (Blustein, 1989). With the exposure of vocational tasks (selecting goals, gathering occupational information, problem solving and self-appraisal), career self-efficacy increases (Hackett & Betz, 1981). Therefore, these strategies can directly enhance toward position outcomes.

Changing Business, "Society" and People – Generally, Generation Z students are expressing an increased interest in changing people and society. However, these aspirations need to be conveyed and connected to technology positions in a defined context. Every position and facet of our society can translate to those ideals by implementing two concepts: 1) reset students' perspective with different metaphors and 2) compiling narratives using direct examples of technology careers can serve a societal purpose. For example, wait staff in restaurants and hotels can provide exceptional and quality customer service to guests daily by enhancing the customer experience on vacation. This interaction would support the instrumental attitude as researched by Moore and Burns (2019).

This outcome can be achieved through training, exposure and role playing to develop awareness as well as operationalize within their careers. Technology is no different. Students can analyze and design platforms (tablets, laptops, etc.) with an interface that can help the wait staff with technology solutions to enhance their job satisfaction and productivity. Students are so immersed in technology use (phones, apps, games, etc.) that they view the strategy of the technology in a similar manner to the <u>*engine*</u> behind driving the car to a destination safely and efficiently. For students, it works, and it does not matter how or why it works.

Interactive Job Fairs and Career Exploration Sessions – Develop and plan sessions to promote technology careers that are staffed with industry personnel; providing a "face" to communicate specific ideas using "real world" examples. The compilation of narratives (printed and online) depicting the emphasizing the previous topics may not be accessed or read. However, the strategy of complimenting these materials with interactive sessions with industry personnel can gain their students' attention. As important, it will also increase their interaction skills that are desperately needed at the present time. The previous strategy discussed the exposure to personnel and careers can add significant value to the exploration process.

Business organizations will agree to volunteer to these events to increase their exposure, build community relations, and (most importantly) develop interest in technology careers for their recruiting efforts. Ainslie (2019) found that companies and practitioners that engage with educational institutions will create a pipeline of workers interested in upward mobility. Ainslie further explains that employers miss opportunities by not engaging in these partnerships. This strategy enables the findings of Rajala (Rajala et al., 2023) which found that the value expectations and value propositions can be gained by participation in outreach activities.

Integration into Curriculum – Educators at all education levels need to be engaged to focus on career exploration. To prepare for job fairs and interaction sessions, homework and in-class assignments can organize various thoughts and ideas for the students prior to interacting with business leaders. Career to Education (CTE) strategies integrated into high schools can provide an environment to "deep dive" into exploration by "doing" and learning and learning immersion. This strategy will dramatically increase the students' knowledge for the career exploration and education decision process by replacing inaccurate stereotypes with objective facts and a hands-on, visual experience. Real-world and hands-on learning activities and projects had a positive effect on students, particularly with female students (Christensen & Knezek, 2017).

7. LIMITATIONS AND FURTHER RESEARCH

Limitations

There are a few limitations from this research study including:

- A few semesters were not included in the survey administration due to the Pandemic and other issues. The lack of data from these semesters limited the number of academic years included in this study.
- Using research, the survey was designed in 2016 and remained consistent over the last six years. No updates or modifications to the survey were implemented to complete a multi-year analysis using several factors and variables with a consistent structure (responses, questions, wording, etc.). It would have been interesting to include additional items such as social media for the media influence factor but may complicate future research studies.
- The responses used for the analysis and conclusions were gathered from only one institution. Using only one institution may not provide an accurate representation of the perceptions investigated in this research study. Students' perceptions and opinions can be influenced by factors due to institutional culture (demographics, geography, socio-economic, size of institution and selectivity of recruiting).

Further Research

As this research study was compiled, one additional idea was uncovered. To replicate this research into a regression for the four academic years using all current factors. Additionally, it may be important to extend the survey administration into the AY2023-24 to gain additional responses. The regression analysis could be completed using the academic year value as a dummy variable in the regression analysis. This research study will amplify the results and outcomes associated with the weights of the several factors on the dependent variable (intent to major).

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Appendix

Occupational Description	Employment (thousands) 2022	2032	Change 2022-32 Number	Percent	Openings Annual Avg 2022-32 (thousands)
Computer and mathematical occupations (summary of 15-0000)	5,277	6,081	803	15.2%	411
Computer and information analysts (15-1210)	700	804	104	14.9%	54
Computer and information research scientists (15-1221)	36	44	8	22.7%	3
Computer support specialists (15-1230)	914	963	49	5.4%	66
Database and network administrators and architects (15-1240)	669	696	27	4.0%	40
Software and web developers, programmers, and testers (15-1250)	2,159	2,628	469	21.7%	179
Computer occupations, all other (15-1299)	449	493	43	9.7%	33
Totals – Computer Occupations	***4,929***	***5,630***	***701***	***14.2%***	***377***

Table 2 – Trends in Information Technology Careers (BLS Table 1.7)

Factor	Research Citations	Factor Category
Aptitude to study information technology	(Epsztajn, 2019; Joshi & Kuhn, 2011; Kuechler et al., 2009, 2009)	AP
Interesting to use; complete work with technology	(Heinze & Hu, 2009; Kuechler et al., 2009; Mims-Word, 2012; Walstrom et al., 2008)	AT
Difficulty of major; requiring significant study time	(Kuechler et al., 2009; Prescod et al., 2018); (Zhang, 2007)	DM
Interest in information technology	(Joshi & Kuhn, 2011; Mims-Word, 2012; Walstrom et al., 2008)	IN
Availability of job positions	(Heinze & Hu, 2009; Joshi & Kuhn, 2011; Walstrom et al., 2008)	JA
Gaining a high starting salary	(Beckhusen, 2016; Joshi & Kuhn, 2011)	JS
Influence of media	(Apostol & Näsi, 2013; Walstrom et al., 2008)	MI
Importance of self-image; image of information technology professionals	(Adya & Kaiser, 2005; Walton et al., 2012)	PI
Social image; considered a respectable career	(Eddy & Brownell, 2016; Walton et al., 2012; Wang & Degol, 2013)	SI
Influence of family, friends, professors, advisors, and peers	(Derricks & Sekaquaptewa, 2021; Joshi & Kuhn, 2011; Walton et al., 2012)	SN
Work environment	(Gill et al., 2008; Joshi & Kuhn, 2011)	WE
Intent to major	(Fishbein & Ajzen, 2010)	IM

Table 3 – Citations for Research Model Factors

Hypothesis	***Hypothesis Definition***
	There are no significant differences between the academic years based on the …
H1	• *aptitude to gain a career in information technology.*
H2	• *attitude toward information technology.*
H3	• *difficulty to major in information technology.*
H4	• *interest in information technology.*
H5	• *availability of information technology positions.*
H6	• *salaries for information technology positions.*
H7	• *influence by various media environments.*
H8	• *personal image of information technology professionals.*
H9	• *social image of information technology professionals.*
H10	• *influence by others relating to information technology careers.*
H11	• *work environment for information technology professionals.*
H12	• *intention to declare information technology as a major.*

Table 4 – Summary of Research Hypotheses

Factor Name	**Number of Questions**	**Question Scale**
Aptitude	2	SD/SA
Attitude	2	SD/SA
Difficulty of Major	2	SD/SA
Interest in IT	5	SD/SA
Job Availability	2	SD/SA
Job Salary	2	SD/SA
Media Influence	5	ENI/EI
Personal Image	2	SD/SA
Social Image	2	SD/SA
Subjective Norm	5	SD/SA
Workload Environment	5	SD/SA
Intent to Major	2	SD/SA
Total	**36**	

Table 5 – Summary of Survey Composition by Factor

Group	**Academic Year**	**Total Responses**	**Percent of Total**	**Male**	**Female**	**Missing, Not Disclosed**
1	2016 – 2017	403	35.7%	241	121	36
2	2017 – 2018	379	33.6%	171	138	68
3	2020 – 2021	169	15.0%	109	50	10
4	2021 – 2022	177	15.7%	125	51	0
	Total	**1,128**	**100.0%**	**646**	**360**	**114**

Table 6 – Frequency of Survey Results

		Mean Values				
Factor	**N**	**2016-17**	**2017-18**	**2020-21**	**2021-22**	**Grand**
AP-Aptitude	1,127	3.42	3.46	3.17	3.43	3.40
AT-Attitude	1,127	4.91	4.74	5.00	5.16	4.91
DM-Difficult of Major	1,126	3.53	3.47	3.46	3.43	3.48
IN-Interest IT	1,127	5.02	4.90	4.92	4.99	4.96
JA-Job Availability	1,127	4.60	4.77	4.48	4.81	4.67
JS-Job Salary	1,127	4.73	4.94	4.77	4.76	4.81
MI-Media Influence	1,127	4.36	4.38	4.17	4.15	4.30
PI-Personal Image	1,127	5.44	5.48	5.64	5.92	5.56
SI-Social Image	1,127	5.32	5.16	5.33	5.55	5.30
SN-Subjective Norm	1,127	2.91	3.06	2.69	2.84	2.92
WE-Workload Environment	1,126	4.84	4.82	4.89	4.97	4.86
IM-Intent to Major	1,125	2.38	2.80	2.31	2.39	2.51

Table 7 – Summary of Group and Grand Means by Factor

Factor		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	
Aptitude	Between Groups	10.303	3	3.434	1.776	.150	ns
	Within Groups	2174.207	1124	1.934			
	Total	2184.510	1127				
Attitude	Between Groups	22.615	3	7.538	4.311	.005	**
	Within Groups	1965.454	1124	1.749			
	Total	1988.069	1127				
Difficulty of Major	Between Groups	1.699	3	0.566	0.546	.651	ns
	Within Groups	1164.247	1123	1.037			
	Total	1165.946	1126				
Interest in IT	Between Groups	3.051	3	1.017	1.015	.385	ns
	Within Groups	1126.109	1124	1.002			
	Total	1129.160	1127				
Job Availability	Between Groups	15.570	3	5.190	3.649	.012	*
	Within Groups	1598.525	1124	1.422			
	Total	1614.095	1127				
Job Salary	Between Groups	9.162	3	3.054	2.371	.069	ns
	Within Groups	1447.739	1124	1.288			
	Total	1456.901	1127				
Media Influence	Between Groups	10.432	3	3.477	2.234	.083	ns
	Within Groups	1744.834	1121	1.556			
	Total	1755.266	1124				
Personal Image	Between Groups	32.288	3	10.763	7.597	.000	***
	Within Groups	1592.350	1124	1.417			
	Total	1624.638	1127				
Social Image	Between Groups	18.016	3	6.005	6.075	.000	***
	Within Groups	1111.076	1124	0.989			
	Total	1129.092	1127				
Subjective Norm	Between Groups	17.099	3	5.700	4.301	.005	**
	Within Groups	1489.561	1124	1.325			
	Total	1506.660	1127				
Workload Environment	Between Groups	3.076	3	1.025	1.355	.255	ns
	Within Groups	849.519	1123	0.756			
	Total	852.595	1126				
Intent to Major	Between Groups	47.443	3	15.814	7.995	.000	***
	Within Groups	2219.450	1122	1.978			
	Total	2266.893	1125				

Table 8 – Summary of ANOVA Test of Significance Results

Factor Category	Category Name	Question Text
AP	Aptitude	Majoring in information technology will be a good fit for me.
AP	Aptitude	I believe that I will perform well in an information technology career.
AT	Attitude	I find computers and technology interesting to use.
AT	Attitude	It is interesting when I use information technology to complete my work.
DM	Difficulty in Major	Majoring in information technology will require more study time.
DM	Difficulty in Major	I believe that I will be able to successfully complete a major in information technology.
IN	Interest in Major	I enjoy learning about technology software.
IN	Interest in Major	I believe that I will enjoy … working in a team
IN	Interest in Major	I believe that I will enjoy … using computer software
IN	Interest in Major	I believe that I will enjoy … presenting business related problems
IN	Interest in Major	I believe that I will enjoy … analyzing business related problems
JA	Job Availability	Upon graduation, the number of information technology jobs will be enough so that I can find a position.
JA	Job Availability	The availability of information technology jobs make me comfortable to maintain a successful career.
JS	Job Salary	I believe that I can secure a high paying job, upon graduating with a major in information technology.
JS	Job Salary	My starting salary will be satisfying if I major in information technology.
MI	Media Influence	For each of the following sources, rate the level of influence on the selection of your major. Career fairs, business presentations
MI	Media Influence	For each of the following sources, rate the level of influence on the selection of your major. Newspapers, magazines
MI	Media Influence	For each of the following sources, rate the level of influence on the selection of your major. Job listings
MI	Media Influence	For each of the following sources, rate the level of influence on the selection of your major. Social media
MI	Media Influence	For each of the following sources, rate the level of influence on the selection of your major. Television, movies
PI	Personal Image	Choosing an information technology major would make me appear to be a nerd or not cool while I am in college.
PI	Personal Image	As an information technology major, people would perceive me as anti-social or boring.
SI	Social Image	Information technology jobs are just for nerds or introverts.
SI	Social Image	Majoring in information technology will lead to a respectable career.
SN	Subjective Norm	My family is encouraging me to choose a majoring in information technology.
SN	Subjective Norm	My friends are encouraging me to choose a majoring in information technology.
SN	Subjective Norm	The opinion of my peers is ...
SN	Subjective Norm	My professors believe that information technology would be a good fit for me.
SN	Subjective Norm	My advisors believe that information technology would be a good fit for me.
WE	Work Environment	I believe that information technology will be a challenging career.
WE	Work Environment	Majoring in information technology will give me the opportunity to obtain a leadership position in business.
WE	Work Environment	Majoring in information systems will give me the opportunity to work on a variety of positions, tasks and activities in business.

Factor Category	Category Name	Question Text
WE	Work Environment	I believe that working in information technology will allow me to be creative.
WE	Work Environment	When working with information technology, I will be able to benefit people in society by what I work on?
IM	Intent to Major	I intend to major in information technology.
IM	Intent to Major	It is likely that I will choose to major in information technology.

Table 9 – Survey Factors and Questions

Developing a Data Analytics Practicum Course

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Abstract

Data analytics is a rapidly growing field that plays a crucial role in extracting valuable insights from large volumes of data. A data analytics practicum course provides students with hands-on experience in applying data analytics techniques and tools to real-world scenarios. This practicum is intended to serve as a bridge between the student's academic environment and the professional application of their skills in an employment and internship setting. This study examined the design of a data analytics practicum course. The main objectives included (1) the identification of topics and skills employers look for in new hires in data analytics-related internships and entry-level positions, (2) the development and implementation of a Data Analytics practicum course and (3) reflection on the first-time offering of the course and suggested improvements for the next iteration. As part of this study, industry and organization survey responses drove the design of the course and development of key student learning gains for five learning modules throughout the semester. Faculty within the departments of information technology (IT), mathematics, and statistics collaborated in the construction, development, and implementation of team-teaching instructional practices of the Data Analytics Practicum in Spring 2023. This study applies an interdisciplinary approach to data analytics practicum development and instruction.

Keywords: Data analytics, practicum, experiential learning, pedagogy, curriculum development, interdisciplinary

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Developing a Data Analytics Practicum Course

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1. INTRODUCTION

There has been an explosion of data analytics and data science programs at colleges and universities both at the undergraduate and graduate levels in recent years. While the two are different degree programs, they share some similarities but also have some distinctions. "… [B]oth work with data, the main difference lies in what they do with it (Burnham, 2021)." The two disciplines both require data mining, programming languages, statistical analyses, problem solving, and data storytelling (Martin, 2020). Data analysts usually perform typical statistical analyses on larger data sets from numerous fields and make use of business intelligence and data visualization tools (Aasheim et al., 2015; Davenport, 2013; Martin, 2020; Viswanathan, 2014). Data scientists are more likely to devise analytical algorithms, model processes and program code, use machine learning, and evaluate the results and implications to make data-driven decisions. (Aasheim et al., 2015; Burnham, 2021; Dumbill et al., 2013; Martin, 2020; Provost & Fawcett, 2013).

Glassdoor Inc.'s (2022) 50 best jobs in America ranked Data Scientist at #3 and Data Analyst at #35. The Occupational Outlook Handbook shows a projected employment growth for the Data Scientist-related professions of 36% between 2021-2031 (Bureau of Labor Statistics, 2023). The Data Analytics degree program was established at our campus due to the increasing demand for graduates with the requisite skill sets for these positions. The degree consists of eight foundation courses, two elective courses, and three experiential courses. One of the experiential courses is a Practicum in Data Analytics. The intended purpose of the practicum course is to prepare upper-level students, majoring in data analytics, for internship and capstone courses. The practicum offers a unique inter-disciplinary opportunity with faculty from mathematics, statistics, and IT.

The research was conducted at a regional campus of an R1 university in Western Pennsylvania. A review of 26 colleges and universities in Western PA revealed that half have programs in data science and/or data analytics either at the undergraduate and/or graduate levels – with one institution requiring a similar practicum experience, and other schools requiring a capstone and/or an internship experience. The main objectives of this study included (1) the identification of topics and skills employers look for in new hires in data analytics-related internships and entry-level positions, (2) the development and implementation of a Data Analytics practicum course and (3) reflection on the first-time offering of the course and suggested improvements for the next iteration. This study contributes to the literature by identifying need, examining pedagogy, and designing of a practicum in the growing field of data analytics (Hartzel & Ozturk, 2022).

2. LITERATURE REVIEW

Data analytics is a rapidly growing field that plays a crucial role in extracting valuable insights from large volumes of data. A data analytics practicum course provides students with hands-on experience in applying data analytics techniques and tools to real-world scenarios. The practicum experience is intended to serve as a bridge between the student's academic environment and the professional application of their skills in an employment and internship setting. These courses aim to bridge the gap between theory and practice by providing hands-on experience with real-world datasets, enhancing students' proficiency in data analytics tools and technologies, deepening their understanding of various data analysis techniques, fostering critical thinking and problem-solving abilities, and promoting effective communication and presentation skills to convey their findings and insights to stakeholders (Alzen et al., 2022). This literature review aims to explore the existing literature on team-teaching practices and data analytics practicum courses, including their objectives, methodologies, and outcomes to understand the key elements that contribute to an effective and successful learning experience.

Team Teaching as an Interdisciplinary Approach

Team teaching is a collaborative method of instruction that has been seen in the literature for decades, with many educational researchers expressing its benefits; yet this instructional methodology is not widely prevalent within undergraduate classrooms (Wadkins et al., 2004; Perignat et al., 2023). It has been used successfully in introductory data science, business, and operations management courses (Asamoah et al., 2015; Ducoffe et al., 2006; Hoefle et al., 2020). Teaching a class with a team of teachers and a staff member benefits educators and students alike. Collaboration allows for diverse expertise and perspectives to be incorporated into the teaching process. The collaborative environment fosters creativity and innovation, through brainstorming teaching strategies and development of course materials. Teachers can bring their unique strengths and specialties, enriching the learning experience by offering different teaching styles, approaches, and knowledge (Hurd & Weilbacher, 2017; Wadkins et al., 2004). Team teaching can improve students' critical thinking, problem-solving, and analytical skills (Austin & Baldwin, 1991; Levy et al., 2006; Little & Hoel, 2011; Yellowley & Farmer, 2005). Moreover, having multiple teachers ensures that students receive individualized attention and support, with greater capacity to provide personalized guidance, and to address specific student needs (Hurd & Weilbacher, 2017). This ultimately helps to facilitate student engagement and critical thinking (Perignat et al., 2023; Roland & Jones, 2020).

Additionally, the workload can be distributed amongst teachers, reducing individual stress, and allowing more time and energy to be invested in lesson planning, promoting student engagement, and overall classroom management. Teacher teamwork can enhance professional growth and development through shared experiences, peer observations, and continuous learning (Hurd & Weilbacher, 2017). By leveraging the collective expertise of a team, the teaching quality and effectiveness can be significantly enhanced, resulting in a more comprehensive and rewarding educational experience for everyone involved.

Practicum Experiences

The use of the practicum experience has been described in fields such as education, nursing, psychology, public health, and other areas (Zeichner, 1990; Clarke, 1995; Ryan et al., 1996; Kolaczyk et al., 2021). Although there is not much literature describing the development of data analytics practicum courses (Hartzel & Ozturk, 2022), it is growing. Literature concerning data science curricula/programs (De Vaux et al., 2017) and for business analytics curriculum development (Ceccucci et al., 2020) exists. There have also been recent developments in offering a practicum in statistics in which students serve as external consultants (Kolaczyk et al., 2021; Paloian et al., 2022). The literature about capstone courses and statistical consulting experiences suggests that students benefit from doing real-world project applications under faculty supervision (Martonosi & Williams, 2016; Paloian et al., 2022). Students learn software packages and "soft" skills like communication. Students also learn the workflow or data analysis cycle of a project (Horton, 2015; Paloian et al., 2022). Unlike a capstone course which typically comes at the end of the program, the practicum can come earlier in the program curriculum (Kolaczyk et al., 2021).

Employer Needs

The design of a data analytics curriculum involves the interplay between academics who develop the curricula, the expert practitioners from industry who provide input to academics and write job descriptions (and hire), and the online occupation services platforms whose advertisements provide data about the job skills requirements (Hartzel & Ozturk, 2022). Faculty can use the skills data and practitioners' expertise to develop their program's courses. Due to the multi-disciplinary nature of data science projects (Hartzel & Ozturk, 2022), some schools have their analytics program in the Information Science Department (Chiang et al., 2012); some in the business department (Wymbs, 2016); and other schools have inter-disciplinary programs (Leman, et al., 2015; Havill, 2019), similar to the one in this study.

Pan et al. (2018) surveyed the advisory boards of the Samford University Business School to determine the characteristics and data analytics skills they desire in graduates. The 50 respondents prioritized five broad areas of study as communication with data, spreadsheet, statistics, data management, and software packages. The chief data aptitudes chosen were obtaining relevant data, documenting data, presenting data, and using basic and intermediate spreadsheet skills.

Using web scraping, Almgerbi et al. (2022) identified seven key job market skill sets in the field of data analytics: business intelligence, data engineering, data science, market analysis, machine learning, software development, and project management. These were found to be among the top key words within job postings. Additionally, the authors identified coding, tools for data analytics, application development, statistical modeling, and machine learning were the most common topics introduced in MOOCs (Massive Online Open Courses) in this field. Understanding these high-demand topics can help students focus their skills accordingly. Also, effective communication and presentation skills were found to be crucial in this domain with students being able to facilitate meetings with communication levels comparable to expert statistical collaborators (Çetinkaya-Rundel et al., 2022; Alzen et al., 2023). Therefore, developing communication and presentation skills becomes an important objective of data analytics practicum courses (Almgerbi et al., 2022).

Employers seek individuals for Data Analytics positions with experience in data visualization, data cleaning, linear algebra, calculus and tool usage skillsets with SQL, Python, R, MS Excel, Tableau, SAS, and Spark (Hu & Cleland, 2019; Johnson et al., 2020). Johnson et al. (2020) also found soft skills of communication, presentation, project management, critical thinking, leadership, management, and negotiation to be highly sought by employers. Practicum courses can introduce students to these analytical methods, business intelligence applications, data collection techniques, analysis processes, and analytic tools (Hu & Cleland, 2019).

Practicum Course Design

Data analytics practicum courses serve various objectives, primarily aimed at equipping students with practical skills and knowledge in data analysis. The Columbia University School of Engineering and Applied Science blog (2019) discussed focused skills sought by employees in Data Analytics including data visualization, data cleaning, MATLAB, R, Python, SQL and NoSQL, machine learning, and linear algebra and calculus. Practicum course design, a comprehensive approach to teaching data analytics, involves introducing students to analytical methods, business intelligence applications, MS SQL, data visualization, and individual projects that encompass data collection and analysis processes and tools used within the field of data analytics. Learning processes should be scaffolded, focusing on key topics, and gradually building up to a final project with evaluation based on projects and an examination (Hu & Cleland, 2019).

Cribbs et al. (2020) identified the skills expected for an optimal, student-centered practicum experience include needs assessments, quantitative and qualitative data collection and analysis, quality improvement projects, and de-identified data analyses. Çetinkaya-Rundel et al. (2022) emphasized the importance of incorporating data analysis and presentation skills in practicum courses, highlighting their crucial role in reinforcing concepts and skills. Consequently, including a project component in the data analytics practicum course is suggested.

Tiahrt et al. (2022) changed their traditional introductory information systems course to a data analytics focused course so "students learn the data acquisition–preparation–mining–presentation process in an information-systems setting" by including additional statistical techniques and data analytics tools. Hu and Cleland (2019) designed a first course in Data Analytics and Business Intelligence. This course introduced students to analytical methods, Big Data, Business Intelligence in practice, data analytics, decision-making, exploration of data with emphasis on the usage of Business Intelligence tools such as MS Excel PivotTables, Power View Reports, and MS Power BI applications. The course also made use of MS SQL Server Integrated Services and Reporting.

In summary, the objectives of a data analytics practicum course are to bridge the gap between theory and practice, develop proficiency in data analytics tools, enhance understanding of data analysis techniques, foster critical thinking and problem-solving skills, and promote effective communication and presentation abilities.

Practicum Evaluation

The outcomes and effectiveness of data analytics practicum courses can be assessed through various evaluation methods. The development of evaluation rubrics is crucial in assessing students' writing, oral presentation, and overall communication skills, catering to both statistical experts and laypersons. Students should demonstrate the ability to critically analyze and interpret data using statistical models and programming skills (Smucker & Bailer, 2015). Additionally, Hu and Cleland (2019) recommend evaluating students based on project development, individual project reports, and exams.

The evaluation of data analytics practicum students can be approached through various methods. First, performance assessment measures students' application of data analytics techniques, their interpretation of results, and their ability to effectively present their findings. This assessment can involve project deliverables, reports, presentations, and demonstrations of technical skills. Second, gathering feedback from stakeholders, such as industry partners or clients who have engaged with student projects, provides valuable insights into the practical relevance and impact of the students' work. Finally, incorporating self-reflection and peer evaluation allows students to reflect on their learning experience and evaluate their peers' performance, facilitating individual growth and assessing the overall effectiveness of the practicum course (Smucker & Bailer, 2015).

The studies referenced in this literature review provide evidence that data analytics practicum courses play a vital role in equipping students with practical skills, knowledge, and experiences in data analysis. By employing project-based learning, collaborative approaches, and industry partnerships, these courses enable students to bridge the gap between theory and practice. Evaluation methods focusing on performance assessment, stakeholder feedback, and self-reflection contribute to measuring the effectiveness and outcomes of the practicum experience.

Continued research in the areas of team teaching, employer needs, and practicum experiences can further enhance the design and implementation of data analytics practicum courses. The current study contributes to the literature in these areas.

3. METHODOLOGY

This study's purpose was to design a data analytics practicum course which meets the needs of local employers and internship sites. A mixed methods approach was used to (1) identify topics and skills employers look for in new hires, (2) develop and implement a Data Analytics practicum course, and (3) reflect on the first-time offering of the course and provide suggestions for improvements for the next iteration. Institutional Review Board approval was received prior to the start of the research study. Surveys administered, module development, and student learning assessments are discussed below.

Community Survey

The development of the Data Analytics Practicum course began with the surveying of local employers to determine the needs for data analysts in Southwestern Pennsylvania. The list of prospective employers was obtained from the Career Services department. The survey included questions concerning industry types, likeliness to hire, data analysis tools used, and desirable skills for incoming interns and/or entry-level hires (see Appendix C). The survey was administered through Qualtrics via email to 156 unique contacts. The contact list was compiled of industries and organizations that had hosted interns from the University within the last five years. Twenty-eight (n=28) responses were received. Survey results were analyzed quantitatively using *SPSS v. 28* software. Responses were used to identify specific skill sets in which employers felt are beneficial for interns and new hires. These results were used to develop a series of modules for a three credit Data Analytics Practicum course.

Module Development

Based on tools and skills identified within the initial community survey, five modules were constructed. These modules introduced career and internship exploration, data ethics, data collection techniques, data cleaning, and data analysis with visualizations. Learning development and skills were evaluated at each module with an assignment that encompassed the main learning goals of each module.

Course Implementation

A three-credit Data Analytics Practicum was team-taught and developed by four faculty members in the Spring Semester 2023 to a small section of upper-level students majoring in Data Analytics (n=4). The faculty consisted of two individuals within the IT Department and two in the Mathematics and Statistics Department, to account for the interdisciplinary nature of the data analytics major. Each faculty member received one-credit remuneration. Once modules were developed, each was co-taught by individuals with expertise in the module's subject area. The course met two times per week for one hour and 15 minutes throughout the semester. Upon completion of each module, students were given an assignment that encompassed the module's content, learning goals, and intended to promote communication and critical thinking skills. The objectives of the course were incorporated into the syllabus and included: (1) to identify data analysis requirements and solutions (2) to apply data science practices and techniques to analyze extensive data sets, (3) to discuss principles for effective data visualization and apply those principles to real-world problems, (4) to apply ethical standards to data extraction (analysis and visualization), and (5) to effectively communicate project methods and explain results in written and oral form (see Appendix B).

Course Requirements
Assignments were created for each module aimed to prepare students for internship experiences and to help students gain skills required to complete an independent research project. Each assignment encompassed the learning goals relating to each module (1) cleaning data, (2) research question proposal, (3) data analysis proposal, and (4) communication skills development through presentations. Instead of exams, each student gave a presentation about his or her project with formal submissions of executive summaries and research papers. The faculty team evaluated final paper submissions based on developed rubrics focusing on student's introductions, methods for data cleaning, methods for data analysis, result presentations, and conclusions (See Appendix E).

Student Learning Gains Survey
Students from the course completed a final survey at the end of the semester. This survey was administered through Qualtrics and evaluated the learning gains listed above and identified students' perceptions of their own growth in technical and soft skills related to data analytics. Open ended questions allowed students to evaluate the course and provide feedback on areas of improvement for subsequent semesters (see Appendix D).

4. RESULTS

This section presents the findings from the community survey, the development of course modules, and the evaluation of student technical and soft skills.

Community Survey Results
Twenty-eight (n=28) responses were received for the Community Survey. Survey results indicate that many respondents were small businesses/organizations (71.4%) representing non-profit (25%), healthcare (14.2%), information technology (7.2%), entertainment (3.6%), manufacturing (3.6%), government (3.6%), education (3.6%), social services (3.6%), and media (3.6%) industry types. Respondents ranged from mid-level employees to presidents of companies. Of those who responded 10.7% reported their place of employment is extremely likely and 10.7% indicated they are somewhat likely to hire a data analyst within the next two years.

The remaining questions in the survey helped to identify both technical and soft skills employers seek for new hires and interns. Overwhelmingly Microsoft products were identified to be the most used within local industries with 50% of industries identifying Microsoft Excel as their primary database or data mining tools and 10.7 % reporting Microsoft Power BI as their primary data visualization software used by interns and personnel. The full list of responses for mining tools, data visualization software, and coding environments is presented in Table 1.

		Frequency (%)
Database or Data Mining Tools	Access	2 (7.1%)
	Adobe	1 (3.6%)
	Amazon RedShift SQL	1 (3.6%)
	Ceridian/Dayforce	1 (3.6%)
	Excel	14 (50%)
	Microsoft SQL Server	3 (10.7%)
	MySQL	2 (7.1%)
	OPTIMA	1 (3.6%)
	Oracle	1 (3.6%)
	Program Specific Software	1 (3.6%)
Data Visualization Software	Ceridian	1 (3.6%)
	Congos	1 (3.6%)
	Microsoft Power BI	3 (10.7%)
	Tableau	2 (7.1%)
	Unsure	1 (3.6%)
	None	5 (18%)
Coding languages and Environments	Excel	11 (39.3%)
	Java	3 (10.7%)
	Python	2 (7.1%)
	R/R Studio	1 (3.6%)
	SPSS	1 (3.6%)
	SQL	1 (3.6%)
	Visual Studio	2 (7.1%)
	None	2 (7.1%)

Table 1: Community Survey on Tools, Software, and Coding Usage

Survey respondents were also asked which technical and soft skill(s) would be most beneficial for interns or potential applicants to have when beginning a position. Based on this question, data visualization (17.9%) and data cleaning and preparation (17.9%) were found to be the top-ranking technical skills. Many respondents identified soft skills such as critical thinking and problem solving (42.9%), communication (50%), both oral and written, and active listening (35.7%) to be most beneficial. A full list of survey results for technical and soft skills is presented in Table 2.

		Frequency (%)
Technical Skills	Creating Dashboards and Reports	2 (7.1%)
	Data cleaning and Preparation	5 (17.9%)
	Data visualization	5 (17.9%)
	Domain knowledge	2 (7.1%)
	Linear Algebra and Calculus	1 (3.6%)
	Machine Learning	3 (10.7%)
	SSQL and NoSQL	1 (3.6%)
	Statistical knowledge and Programing	2 (7.1%)
Soft Skills	Active Listening	10 (35.7%)
	Communication (Written and Oral)	14 (50%)
	Critical Thinking and Problem solving	12 (42.9%)

Table 2: **Beneficial Technical and Soft Skill(s) for Interns or Potential Applicants**

Practicum Course Development

Based on tools and skills identified within the initial employer survey and literature review, five modules were constructed. These modules introduced themes relating to career and internship exploration, data ethics, data collection techniques, data cleaning, and data analysis with visualizations. Throughout each module, students were allotted time to actively work on projects in which they could have a hands-on experience practicing each concept introduced with faculty present to individually consult as questions arose. Learning development and skills were evaluated with an assignment that encompassed the main learning goals of each module.

The following outlines the 16-week semester and module summaries (see Appendix B):

Week 1: Syllabus and Course Introduction
Week 2-3: Module 1
Week 4-5: Module 2
Week 6-7: Module 3
Week 8-11: Module 4 (including spring break)
Week 11-14: Module 5
Week 15: Independent Project Work
Week 16: Project Presentations (Finals week)

Module 1: Career and Internship Exploration was developed in collaboration with the campus career services to allow students to examine career options, gain experience in resume writing, creation of cover letters, and interviewing. Students gained information about skills, experience, and qualities that employers are seeking in entry-level candidates within the field. After focusing on applicant preparation for one week, each student was also given the opportunity to meet individually with a staff member from the Office of Career Services to discuss any questions or areas of interest they chose for guidance and/or practical application.

Module 2: Data Ethics was developed to give students insight into ethical decision making, reproducibility of data collection/analysis, and responsible reporting. Students were given the opportunity to critically evaluate published works in class, introduced to documentation tools, the importance of documentation and transparency to support ethical conduct, and additional online learning resources and modules.

Module 3: Data Collection was developed to introduce several types of data as well as data resources. This included the evaluation of data resources used by data analysts, common data classifications in statistics, data structures in coding, study design and data collection techniques.

Module 4: Data Cleaning was developed to introduce students to commonly used data cleaning techniques using Microsoft Excel and SPSS. This allowed students to gain hands-on experience with different data formats and with the use of Excel functions and SPSS syntax coding. This module included information on cosmetic cleaning, checking for errors, importing, and exporting various file formats, and recoding variables.

Module 5: Data Analysis was developed to give students an introduction to several types of data analysis and visualization software/tools using SPSS, Excel, Power BI, and Tableau. Students were also introduced to concepts of diagnostic, cognitive, predictive, and prescriptive data analysis techniques.

Final Project: The culmination of the course resulted in a final project to tie together information and skills developed from module 2 through module 5 with faculty mentoring throughout the semester. This project allowed students to gain hands-on experience in completing, writing, and presenting a research project within the field of data analytics.

Student Demographics and Incoming Skills

The Data Analytics practicum was offered in Spring 2023 to the first cohort of data analytic majors (n=4). These students were sophomore level or above. All students had completed or were currently enrolled in introductory courses in information systems, database management, linear algebra, statistics, and regression. Seventy-five percent of the students completed coursework in finite mathematics and principles of data science. Half of the students had completed courses in Python. None of the students had taken elective courses in data visualization or geospatial information systems. The courses listed above are requirements for the major. Incoming students identified prior exposures to Microsoft Excel (75%), Microsoft

Power BI (25%), SPSS (100%), Tableau (50%), and R (100%).

Changes in Student Skills

The final survey measured student perceptions of changes in technical and soft skills from studying the modules in the course (see Appendix D). The course modules supported students learning additional skills with Excel, SPSS, Power BI, and Tableau. Students overall felt the same familiarity, somewhat more familiar, or much more familiar with the mentioned programs based on Likert scaled responses, as seen in Appendix A (Figure 1).

Students' comfort level for each of the measures ranged from feeling neutral on program usage, somewhat comfortable, or extremely comfortable based on Likert scaled responses, as seen in Appendix A (Figure 2).

Students in the course were asked within the final survey to evaluate their own confidence in their abilities to perform tasks such as cleaning data, analyzing data, and presenting research and results. Students overall answered that as a result of the course they viewed their ability had increased (somewhat more or much more) as a result of the learning modules within the course. Complete responses can be seen in Appendix A (Figure 3).

To gain more in-depth understanding and feedback from students about the course, open-ended questions were incorporated into the final survey to allow students to evaluate what aspects of the course were most beneficial and indicate areas of improvement. Student comments indicated that students enjoyed the module aspects of the course and the building of a final project as an iterative process. Students also indicated that the reviews of Excel and SPSS and overviews of Tableau and Power BI were beneficial to further their familiarity and ability to use these programs. Students also identified that they enjoyed the interactive "labs" within each module which furthered their understandings. Students provided feedback that they would like more hands-on examples during class time outside of project work, more time to collectively discuss, and more independent workdays for each module.

5. CONCLUSION

The field of data analytics is experiencing rapid growth and is increasingly important in extracting valuable insights from large amounts of data. A data analytics practicum course offers students a valuable opportunity to gain hands-on experience by applying data analytics techniques and tools to real-world situations. This study focused on designing such a practicum course, aiming to identify the topics and skills sought by employers in data analytics internships and entry-level positions, develop and implement the course, and reflect on its initial offering for future improvements. Results enabled a better understanding of local industry and organization needs in terms of job/internship opportunity growth in Southwestern Pennsylvania. With over 21% of the surveyed companies and organizations indicating their likeliness to hire data analytics-related positions within the next two years, the development of practicum experiences helps to better train students for these opportunities.

Scholarly research in developing a data analytics practicum is in its infancy (Hartzel & Ozturk, 2022), and it is necessary to draw on the studies from related disciplines such as statistics to understand the best practices in this form of pedagogy. A gap exists in the literature as to how to best prepare a student for a data analytics practicum experience, and our study helps to address that gap by providing a tested outline for course design aligned with employer and student expectations and based on similar industry best practices. This study contributes to the literature in terms of the design and implementation of data analytics practicum courses. Practicum experiences help to prepare students for the challenges and opportunities seen within data analytics-related internships and careers. Community Survey results were consistent with literature in terms of sought-after soft and technical skills (Johnson et al., 2020; Tiahrt et al., 2022). Employers need interns who have developed both the analytical capability to analyze data and the knowledge of the commonly used tools to perform that analysis and present the findings. These tools include Microsoft Excel, Tableau, and Power-Bi for small to medium-sized employers.

Since faculty aligned the course with the expectations and needs of employers, students who participate in this practicum will be better prepared for the professional application of their skills in employment and internship settings. The hands-on nature of the practicum allows students to bridge the gap between their academic environment and the practical demands of the work force. This study developed an interdisciplinary, team-taught, module-based data analytics practicum which could be implemented at other undergraduate institutions.

Students benefited from team-teaching as the primary method of instruction. Team-teaching enabled the practicum to cover a diverse, interdisciplinary set of topics. Based on the team-teaching structure, students received individualized support throughout the semester, with hands-on in-class activities, discussions, and project development. The faculty benefited by building a greater rapport with each other and gaining exposure to different teaching techniques and diverse thoughts.

A well-designed data analytics practicum focuses on careers and job types, identifying data sources, analyzing data which includes obtaining and cleaning data, and presenting findings. Using videos, assigned readings, class discussions, and face-to-face lectures, provides the foundation of learning. Individual student projects, using active learning, synthesizes their understanding and prepares them for an internship experience. While this study laid the foundation for the Data Analytics Practicum, there is room for continuous improvement in future iterations. The insights gained from this initial study as well as future data collected can aid future course development, ensuring that the course remains up to date in the growing field of data analytics.

Study Limitations

The primary study limitation involves the use of surveys for data collection so results may not be generalizable. Sample size was a limitation. Of the 156 invited participants for the Community Survey, only 28 unique responses were obtained. These respondents tended to work for small businesses or organizations; therefore, may not be working with large datasets, and may not be representative of all organizations with data analytics needs. The community survey was voluntary and required individuals to self-report based on their own understandings and knowledge which may not have been representative of the company as a whole. Additionally, the first cohort of data analytics majors eligible to take the practicum course consisted of four students. Students were asked to self-report skill development and may have been reluctant to express opinions while currently enrolled in the course and the small class size limited generalizability. Another limitation was that half of the students enrolled in the practicum had not completed all prerequisite courses which required additional instruction to fill gaps in their knowledge. Some additional class periods were needed for the Data Cleaning and Analysis modules and project work.

Future Research

One possibility for future studies is to compare the first offering of the practicum to future offerings, in which students have all prerequisite courses completed. Future research is also needed focusing on the pedagogy and implementation of data analytics practicum experiences in larger classrooms. Longitudinal studies could aid in gaining a better understanding of the benefits of a practicum course on student's internship experiences and provide additional suggestions for course revisions for future offerings. Additionally, a pre- and post-test assessment of confidence and knowledge in subject areas introduced in the practicum could be used to better assess knowledge gained throughout the course.

6. ACKNOWLEDGEMENTS

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Appendix A
Figures from Practicum Final Survey Data

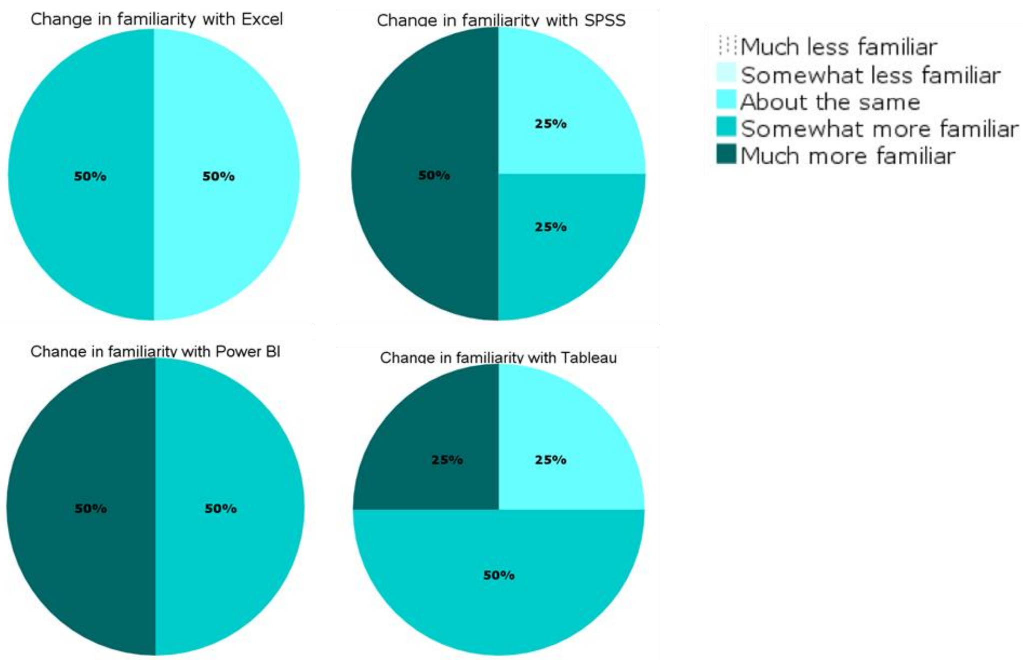

Figure 1: Changes in Familiarity with Tools

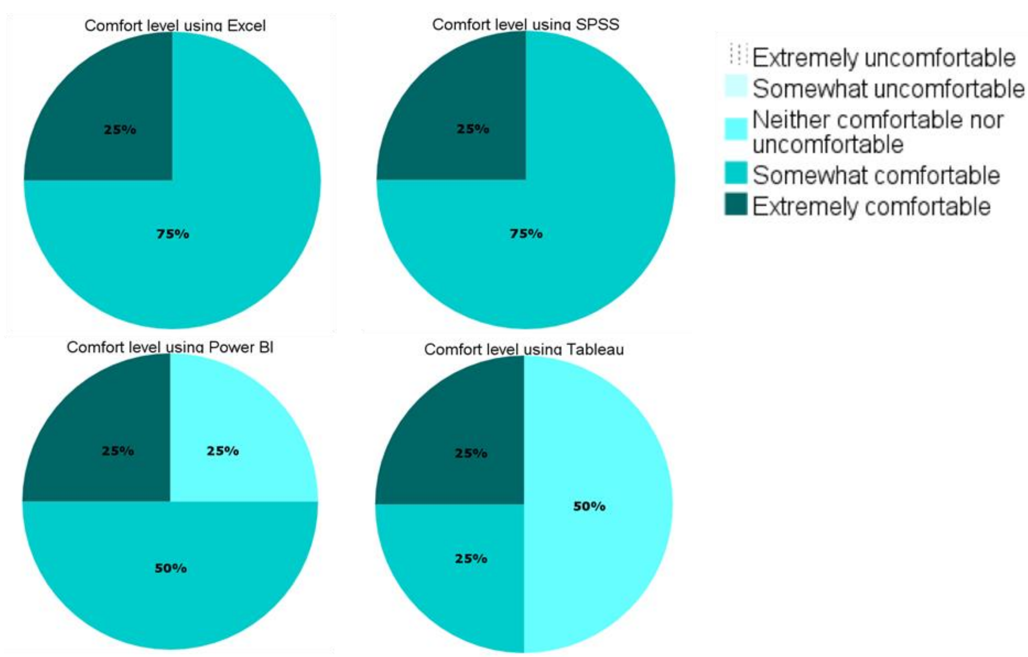

Figure 2: Changes in Comfort with Tool Usage

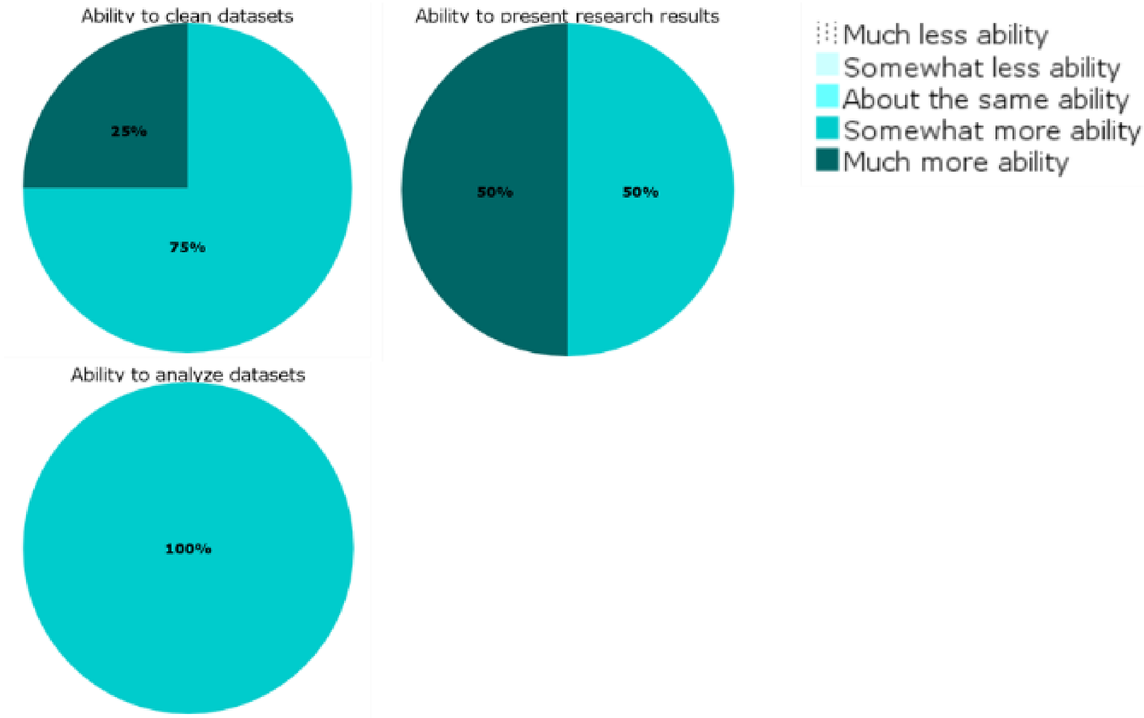

Figure 3: Student Self-reported Changes in Ability (Skills)

Appendix B
Example Course Syllabus

Data Analytics Practicum

Spring 2023

Class Meeting: MW 3:00PM – 4:15PM Classroom: Powers Hall 120

Instructors:

Dr. Neelima Bhatnagar:
E-mail: bhatnagr@pitt.edu
Office Hours: *by appointment**
Office: Powers Hall 124

Dr. Victoria Causer:
Email: vdc5@pitt.edu
Office Hours: *by appointment**
Office: Powers Hall 127

Dr. Michael Lucci:
Email: mlucci@pitt.edu
Office Hours: *by appointment**
Office: Cassell Hall 237

Prof. Michael Pry:
Email: mip84@pitt.edu
Office Hours: *by appointment**
Office: FOB 105

*You can also schedule other office hours with any instructor through email.

Course Description

Students will be introduced to learning modules, based on various topics in data analytics, in preparation for projects, internships, or job experiences. Students will develop the skills necessary to understand, interpret, and analyze data based on multi-disciplinary approaches in data analytics.

Data Science Practicum (PREQ: Regression, Python, Database management systems) is to be completed prior to completion of junior year.

Required Materials

All materials will be provided by instructors and posted on canvas.

Software used in class is available through The University's Virtual Lab and available for download using the Software Download Service.

Course Objectives

Upon successful completion of this course, the student will be able to:

- Identify data analysis requirements and solutions. i.e., what decisions need to be made, what data is available to help, how should data be presented?
- Apply data science practices and techniques to analyze extensive data sets.
- Discuss principles for effective data visualization and apply those principles to real-world problems.
- Apply ethical standards to data extraction (analysis and visualization) and communicate results.
- Effectively communicate project methods and explain results in written and oral form

Course Requirements & Grading

- Attend class and be on time.
- Participate in class discussions and activities.
- Complete learning modules and corresponding assignments.
- Complete final project.

Final course grades will be assigned based on the percentages listed below.

Course Assignment	Weight
Attendance and Participation	10%
Module 1	15%
Module 2	15%
Module 3	15%
Module 4	15%
Module 5	15%
Final Project	15%
Total	**100**%

The scale used to calculate the final course grade is as follows (based on overall percent):

A+: 100 A: 93-99 A-: 90-92	B+: 87-89 B: 83-86 B-: 80-82	C+: 77-79 C: 73-76 C-: 70-72	D+: 67-69 D: 63-66 D-: 60-62	F: 0-59

Modules and Assignments

INFSC 1851 and STAT 1851 are cross listed as a requirement for the Data Analytics Major. This practicum will be organized into modules which introduce students to interdisciplinary topics and programing in statistics and information science that will be beneficial for internships and capstone.

The following modules will be covered throughout the semester (more details are provided in the tentative schedule). Each module will have corresponding assignment(s) that reinforce concepts introduced in class. Rubrics and descriptions for assignments will be provided throughout the semester.

- **Module 1: Career and Internship Exploration**
- **Module 2: Data Ethics**
- **Module 3: Data Collection**
- **Module 4: Data Cleaning**
- **Module 5: Data Analysis Miscellaneous concepts**
- **Final Project: Paper and presentation**

Weekly Schedule & Due Dates

Week	Date	Class	Assignment Due	Faculty
1	M Jan 9	Syllabus and Introductions		All
	W Jan 11	Data Analytics v. Data Science		All
2	M Jan 16	MLK Day - No classes		
	W Jan 18	Module 1: Career and Internship Exploration Resumes & Cover letters		IT/Career Services
3	M Jan 23	Interviewing, Networking, & Professionalism		IT/Career Services
	W Jan 25	Class time for individual appointments	Career Service Appointments	
4	M Jan 30	Module 2: Data Ethics LinkedIn Learning	Resume, Career Assignment	IT/STAT
	W Feb 1	LinkedIn Learning		IT/STAT

5	M Feb 6	Reproducibility & Responsible reporting		STAT
	W Feb 8	Documentation of Study		STAT
6	M Feb 13	Module 3: Data Collection Types of Data	Executive Summary	IT/STAT
	W Feb 15	Data Resources, Project Ideas, & Examples		IT/STAT
7	M Feb 20	Project development work		IT/STAT
	W Feb 22	Project Proposal Presentations	Proposal Presentations	All
8	M Feb 27	Module 4: Data Cleaning Lab 1 Excel		STAT
	W Mar 1	Lab 2 SPSS		STAT
9	Mar 5- Mar 12 Spring Break – No classes			
10	M Mar 13	Project Data work		STAT
	W Mar 15	Module 5: Types of Data Analysis	Clean Data and Summary	IT
11	M Mar 20	DA tools		All
	W Mar 22	Data Analysis Techniques		STAT
12	M Mar 27	Data Analysis Techniques		STAT
	W Mar 29	Lab 1 (SPSS)		STAT
13	M Apr 3	Lab 2 (Excel)		STAT
	W Apr 5	Lab 3 (Power BI)		IT
14	M Apr 10	Lab 4 (Tableau)	Analysis Plan	IT
	W Apr 12	Module 5: Project work		All
15	M Apr 17	Module 5: Project work		All
	W Apr 19	Module 5: Project work		All

Appendix C
Community Survey Questions

Data Analytics Skills Practicum Study

Q2 Which of the following categories best represent(s) your organization? (Select all that apply)
Business
Healthcare
Entertainment
Manufacturing
Government
Information technology
Software Development
Education
Social Services
Non-Profit
Other (Please list)

Q3 Which of the following categories best describes the organization you work for?
Small business (Less than 1500 employees)
Mid-market enterprise (1500 to 2000 employees)
Large enterprise (More than 2000 employees)
Other (Please list)

Q4 What is your current relationship to your organization?
Entry-Level
Mid-level Employee
Manager
Director
Vice-President
Chief Executive Officer
Chairperson and/or Board of Directors
Other (Please list)

Q5 Which of the following categories best describes your organization's likeliness to hire a data analyst type position within the next 2 years?
Extremely unlikely
Somewhat unlikely
Neither likely nor unlikely
Somewhat likely
Extremely likely

Q6 Which of the following Database or Data Mining Tools do your Data Analytics interns/personnel use? (Select all that apply)
Access
Excel
Microsoft SQL Server
Oracle
MySQL
Other (Please list)

Q7 Which of the following Data Visualization Software do your Data Analytic interns/personnel use? Please select all that apply.
Apache Spark
Cognos
ElasticSearch
Graphana
Kibana
Logstash

Microsoft Power BI
QuikTech QuickView
Tableau Software
TIBCO Spotfire
Other (please enter)

Q8 Which of these coding languages/environments do your Data Analytics interns/personnel use? Please select all that apply.
Java
Python
R / RStudio
SAS
SPSS
Visual Studio
Excel
Other (please enter)

Q9 Which of the following do you believe are the most beneficial technical and soft skill(s) for interns or potential applicants to have when beginning a position? (Select all that apply)
Data Visualization
Data Cleaning and preparation
Statistical knowledge and Programing
SQL and NoSQL
Machine Learning
Linear Algebra and Calculus
Creating dashboards and Reports
Critical Thinking and Problem Solving
Communication (Written and Oral)
Active listening
Domain knowledge
Other (Please list)

Appendix D
Student Learning Gains Survey Questions

Data Analytics Practicum Final Survey

Q1 Prior to starting practicum, which of the following computer software packages were you familiar with? (Check all that apply.)
Microsoft Excel
Power BI
SPSS
SAS
Tableau
R
Other (please list)

Q2 Based on experience in this class, which of the following describes your overall change in familiarity with Excel?
Much less familiar
Somewhat less familiar
About the same
Somewhat more familiar
Much more familiar

Q3 Based on experience in this class, which of the following describes your overall comfort level using Excel?
Extremely uncomfortable
Somewhat uncomfortable
Neither comfortable nor uncomfortable
Somewhat comfortable
Extremely comfortable

Q4 Based on experience in this class, which of the following describes your overall change in familiarity with SPSS?
Much less familiar
Somewhat less familiar
About the same
Somewhat more familiar
Much more familiar

Q5 Based on experience in this class, which of the following describes your overall comfort level using SPSS?
Extremely uncomfortable
Somewhat uncomfortable
Neither comfortable nor uncomfortable
Somewhat comfortable
Extremely comfortable

Q6 Based on experience in this class, which of the following describes your overall change in familiarity with Power BI?

Much less familiar
Somewhat less familiar
About the same
Somewhat more familiar
Much more familiar

Q7 Based on experience in this class, which of the following describes your overall comfort level using Power BI?

Extremely uncomfortable
Somewhat uncomfortable
Neither comfortable nor uncomfortable
Somewhat comfortable
Extremely comfortable

Q8 Based on experience in this class, which of the following describes your overall change in familiarity with Tableau?
Much less familiar
Somewhat less familiar
About the same
Somewhat more familiar
Much more familiar

Q9 Based on experience in this class, which of the following describes your overall comfort level using Tableau?
Extremely uncomfortable
Somewhat uncomfortable
Neither comfortable nor uncomfortable
Somewhat comfortable
Extremely comfortable

Q10 Based on experience in this class, which of the following describes your overall change in comfort of your ability to clean datasets?
Much less comfortable/able
Somewhat less comfortable/able
About the same comfort/ability
Somewhat more comfortable/able
Much more comfortable/able

Q11 Based on experience in this class, which of the following describes your overall change in comfort of your ability to analyze datasets?

Much less comfortable/able
Somewhat less comfortable/able
About the same comfort/ability
Somewhat more comfortable/able
Much more comfortable/able

Q12 Based on experience in this class, which of the following describes your overall change in comfort of your ability to present research results?

Much less comfortable/able
Somewhat less comfortable/able
About the same comfort/ability
Somewhat more comfortable/able
Much more comfortable/able

Q13 Which aspects of practicum do you feel were most beneficial in your preparation for the work force and why?

Q14 Do you have any suggestions to improve the course?

Appendix E
Final Project Description and Rubric

Project Description:

The final paper should **tie all the previous assignments together** as a formalized paper. The final paper should be in APA format (formatting and citations), written in third person, and make use of proper grammar and full sentences.

The report should include the following sections:

- **Introduction:**
    - Describe the topic you are examining (include 2-3 references)
    - Purpose of project/Research question
- **Data description (Module 3)**
    - Where data was found
    - Variables included
    - Variable description
- **Data cleaning (Module 4)**
    - Program(s) used to clean
    - Process of cleaning
    - Description of dataset used for analysis
- **Data Analysis (Module 5)**
    - Program(s) used to analyze
    - Description of analysis (e.g., Descriptive statistics, formal tests, visualizations)
- **Results:**
    - Tables and visualizations resulting from analysis
    - Include titles for tables and figures using APA formatting
- **Discussion/Conclusion:**
    - Description of results tables and figures
    - What do the results mean with respect to research question(s)?
- **References**

Grading Rubric:

Criteria	Ratings				Pts
Introduction	**5 pts Full Marks** Proper use of sources and description of research topic. Clear research question. Use of 2-3 sources. Use of full sentences with no/minor grammatical errors.	**3 pts Partial** More detail needed to explain research area. Did not include 2-3 sources. Clear research question.	**1 pts Partial** Only contains research question	**0 pts No Marks** Missing	/5 pts

Criteria	Ratings					Pts
Data Description	**5 pts Full Marks** Detailed data description. Contains information on sources of data, variables included, and variable description.	**3 pts Partial** More detail needed. Only describes two of three pieces of information	**1 pts Partial** More details needed. Focus only on one aspect of the information that was to be listed.	**0 pts No Marks** Missing		/5 pts
Data Cleaning	**10 pts Full Marks** Fully describes the data cleaning process including program(s) used, process, and clean dataset description used for analysis. Written using full sentences and proper grammar.	**8 pts Partial** More details needed to describe data cleaning process including program(s) used, process, and clean dataset description used for analysis (e.g. only discussing two of three items).	**6 pts Partial** Bulleted points. Section not written using full sentences and proper grammar.	**3 pts Partial** Bulleted points. Missing some aspects of section.	**0 pts No Marks** Missing	/10 pts
Data Analysis	**10 pts Full Marks**	**5 pts Partial**	**3 pts Partial**	**0 pts No Marks**		/10 pts

Criteria	Ratings					Pts
Results	**10 pts Full Marks** Tables and visualizations resulting from analysis Included titles for tables and figures using APA formatting.	**7 pts Partial** Tables and visualizations resulting from analysis Does not include titles for tables and figures using APA formatting	**5 pts Partial** All results not presented	**0 pts No Marks** Missing		/10 pts
Discussion/Conclusion	**10 pts Full Marks** Full explanations of results tables and figures. Clearly described what results mean in respect to research question. Use of full sentences and proper grammar.	**8 pts Partial** Some confusion on interpretation of results tables and figures. Clearly described what results mean in respect to research question.	**6 pts Partial** Some misinterpretations of results tables and figures. Some confusion on what results mean in respect to research question.	**3 pts Partial** More explanation needed. Does not relate results back to research question.	**0 pts No Marks** Missing	/10 pts
Total Points: ________/50						

Teaching Case

The Agile Student Practice Project: Simulating an Agile Project in the Classroom for a Real-World Experience

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Abstract

In response to the adoption of Agile practices and processes by businesses, IT/IS educators are working to add Agile content to their courses. Teaching students about Agile involves teaching them about the history, mindset, and values of Agile, along with an introduction to the practices and processes used in an Agile product. Along with this, it is essential that students gain experience using Agile in a project setting. This paper discusses an Agile practice project where students use all aspects of Agile to address a problem and build a solution using Legos. The use of Legos, along with a project that students can easily see themselves using, the practice project allows students to focus on developing their Agile skills and mindset. The project serves as a useful transition from traditional classroom instruction about Agile to a project for a real-world client.

Keywords: Agile, active learning, collaboration, Agile project.

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The Agile Student Practice Project: Simulating an Agile Project in the Classroom for a Real-World Experience

David M. Woods and Andrea Hulshult

1. INTRODUCTION

Over the last decade, Agile emerged as a new organizational paradigm (Ahgina, De Smet, Lackey, Lurie, & Muraka, 2018) for organizations of all sizes across diverse sectors (Babik, 2022). ICAgile, an organization that supports learning and certification related to Agile, defines Agile as “a mindset that welcomes uncertainty, embraces challenges, empowers individuals, and views failure as a learning opportunity” (ICAgile, Mission, n.d.). The popularity of Agile emerged before the COVID-19 pandemic and continues to be an attractive solution to help organizations respond and adapt to change. The pandemic disrupted supply chains, retail markets, and even how people collaborate (from in the office to virtual) (Hulshult, A., & Krehbiel, T.C., 2021). We live in a Volatile, Uncertain, Complex, and Ambiguous (VUCA) world, which requires an approach that helps mitigate the chaos, stress, and anxiety that comes along with volatility, uncertainty, complexity, and ambiguity. The Agile mindset, principles, and practices welcome uncertainty, embrace challenges, and view failure as a learning opportunity (Hulshult, A., & Krehbiel, T.C., 2021).

To better prepare students for the Agile workforce, an IS/IT education program at a public university incorporated the Agile mindset and the Agile way of working into its curriculum. As part of its three-course Agile concentration, students gain Agile foundational knowledge and practical experience in applying Agile to the workplace. This three-course Agile concentration is also accredited by the International Consortium for Agile (ICAgile), and each course provides students with the opportunity to earn an ICAgile industry certification (Hulshult, A., & Woods, D., 2020).

The initial course in the sequence provides students with their first introduction to Agile. The initial part of the course discusses the history of Agile and the motivation behind it, introduces the idea of the Agile mindset, and introduces the main Agile principles and practices. In the later part of the course, students are broken into teams and complete a project for a real-world client that provides students with experience working with Agile.

Bridging the gap between these two parts of the course is a challenge. In the initial work, in-class activities are used to introduce students to specific Agile practices. However, these do not provide students with the experience and comfort level needed to work productively with the client at the start of the client project. An activity that will allow students to focus on using the Agile process to solve a problem while developing an Agile mindset, while limiting the effort students devote to understanding the problem they are solving and the tools used to build the solution is needed. While many instructors have written about activities they use to teach Agile, none of the published work fit this need, so a new Agile Practice Project activity was developed.

2. BACKGROUND

With the growth of interest in Agile, IT/IS educators have been working to develop and assess activities for teaching Agile concepts. Presenting activities that reinforce Agile and Scrum fundamentals can be challenging; however, research indicates that when Agile theory is combined with a hands-on activity, learning is more effective than just lecture or video alone. A literature survey located various classroom activities used to reinforce Agile and Scrum fundamentals and practices.

Valle and O’Mara (2015) developed an activity that teaches Agile fundamentals in undergraduate, graduate, and executive education project management courses to introduce participants to the fundamentals of Agile. Their activity divides students into teams and presents them with a project to work on, which involves completing different types of lists (such as listing the state capitals or famous people named “David,” etc.). The teams work on completing these lists by working in sprints and using Scrum practices. This activity is a short activity with sprints lasting 2 minutes.

Sibona, Pourreza, and Hill (2018) conducted a study using two different approaches to teach

Agile and Scrum principles to business students. One lesson was lecture-focused, and the other activity-focused. Their research indicates that students' perception of Agile increased when they had the lecture and then the activity. For this activity, students are provided with origami paper and instructions. The students work in teams to follow the instructions. This activity is another short activity with 5-minute sprints.

In order to teach Scrum concepts to undergraduate students, Barcelos Bica and Silva (2020) use an activity to build a city with Lego blocks. Barcelos Bica and Silva use this Lego activity in a workshop format. Their research indicates that games and activities are more effective than theory or video lessons. This exercise is a longer activity, but students are provided user stories and other material to allow the activity to focus on the Agile development process.

In a first-year computing concepts course, Frydenberg, Yates, and Kukesh (2018) use a brief simulation game where students design, build, and test paper airplanes to introduce first-year computing students to agile principles and waterfall concepts. Students work in teams to experience both agile principles and waterfall concepts while designing and building paper airplanes. Their research indicates that this paper airplane simulation helps students learn the roles and approaches of both methods.

May, York, and Lending (2016) use the “Ball Game” in a Systems Analysis and Design course to help students experience the effects of a self-organizing Scrum team. The Ball Game is introduced after students learn about the Scrum framework. Besides helping students to experience a self-organizing team, the brief Ball Game activity also provides an opportunity to discuss other elements of the Scrum framework, such as agility, feedback, and estimation.

In a Systems Analysis and Design course, instructors use a simulated project over the course of the semester to learn Scrum principles and practices (Baham, 2019). For this Scrum project, students develop a working piece of software that integrates with a database. Weeks 8-16 of the course are where students work in two-week sprints to develop the project. This simulation helps students to gain real-world Scrum experience (Baham, 2019).

These are valuable activities to introduce various aspects of Agile that fall into two groups. One set is short activities that focus on introducing a small set of Agile practices in a single class meeting without requiring students to use technical skills such as programming. The other activities involve a longer project but require students to have significant technical skills (Baham, 2019; Babik, 2022) or focus on just the Agile development process (Barcelos Bica & Silva, 2020). Missing is an activity where students the full Agile planning and development process to complete a multi-week project without needing significant technical skills.

3. DESIGN

The Agile Practice Project (APP) activities were designed to connect the initial part of the course, where students were introduced to Agile, with the final part of the course, where students apply and develop their Agile skills and mindset by working on a client project. In the initial part of the course, students are introduced to the history of Agile, the Agile mindset, along with Agile practices and processes that support a customer focus, planning, delivery, leading, monitoring work, and delivering quality. These concepts are covered through lectures, small group discussions, and activities where students worked with individual Agile practices such as writing a focusing question, identifying user personas, documenting features using user stories, feature estimation and prioritization, release planning, acceptance criteria, and many more. Additionally, students are introduced to tools and techniques commonly used in Agile, including planning poker, social contracts, Kanban boards, and Trello. During the initial part of the course, the focus is on introducing individual concepts. While they are discussed as part of the overall Agile process, the main effort is for students to gain a basic understanding of each concept, with limited effort to connect all of the concepts as part of an overall project since this is one purpose of the client project.

During the final part of the course, student teams will work with a client to develop a product for the client. At the start of this project, the student teams must be ready to interact with the client to learn about the client’s needs, document requirements for the client’s product, and quickly deliver value. The APP is designed to give students experience working through an entire project using Agile to allow them to see how different Agile practices and processes are connected. Working through the entire Agile process in a practice project allows students a place to practice and refine their knowledge of Agile in a low-stakes environment. Students can then start the client project and focus more on the client's needs with fewer concerns about their understanding of Agile practices.

Another consideration was to have an active learning activity in multiple senses of the word active. Ideally, the project would be hands-on and would get students out of their chairs and moving around in the classroom to bring energy to the activity. This would encourage interaction and collaboration between the students and support team building.

The use of Legos is an ideal solution for providing a hands-on project. Building with Legos gives students immediate satisfaction from seeing progress on the project. Additionally, the connections and interactions between the tasks individual students were working on would be easily visible, prompting communication and collective decision-making, which are key aspects of Agile teams. Lego kits also provide a varied but limited set of blocks, forcing teams to communicate and prioritize to share resources. A project that built a physical object would also simplify the Agile showcase that occurs at the end of each iteration and makes it easier for the instructor and other students to provide clear feedback.

A couple of constraints had to be addressed in designing the APP. The first constraint was time. While the APP was important in solidifying students' knowledge of Agile, giving students a start-to-finish view of an Agile project, and preparing them for the client project, the time allotted for the APP needed to fit into the overall schedule for the course. A second constraint was the knowledge and skills students could apply to the APP. Since the course is designed for first- or second-year IT students and was also open to students from all majors, the instructors could not expect students to have a consistent set of technical skills, for example, building with Lego blocks. A final consideration for the APP was choosing a project that students might use, making it easier for students to understand the customer's needs, identify requirements, etc.

To address these requirements and constraints, the APP is based on a fictional news release that a recent survey shows that local residents and students report a need for a family-oriented entertainment center in the area. As local residents and consumers of entertainment, students will be users of this product, so they should be able to propose features for a solution and document how features will provide business value. To address the skills concern and the limited time frame, students will implement their solutions using Legos. For online courses, online, multi-user design tools such as TinkerCad or Minecraft can be used.

4. IMPLEMENTATION

The Agile Practice Project starts by sharing a fictional news release (see Appendix A) with the teams. Teams are told that they will design a product to meet these needs and will then build it using Legos. After an initial discussion of the project, teams used Agile practices to work through the concept and initiate phases of the project. The main activities and the timebox set for each activity are listed in Appendix B. A presentation (available as teaching notes) is used to support the activities. For each activity, a slide states the activity's timebox and what teams need to work on. For each activity, a couple of slides are also included to provide a quick review of content relevant to the task.

While the teams work on each item, the instructor circulates amongst the teams to listen in on their discussions and provide coaching as needed. After each timeboxed activity, there is a short class discussion. One team may be asked to share their work, the instructor may share comments based on individual team discussions they heard, or teams may ask questions.

The team starts by developing ideas for the product. Each team member provides one or more ideas written on Post-it notes. Next, the teams select one idea as their product using techniques such as horse racing, introduced earlier in the semester. As part of this process, teams are encouraged to check whether they are happy with the selected idea and, if not, to do more brainstorming. Once the team has settled on a project idea, the team member who contributed the idea is identified as the customer for the team's project and will fill this role, with assistance from the instructor for the rest of the project.

After identifying a project idea, the teams create a focusing question to focus the team on a common objective. After the focus question has been written, each team works with their customer to sketch out a high-level solution on the team's whiteboard and also creates a list of the product's main features. These sketches and lists were saved so that teams could refer back to them throughout the project. This step also allowed the instructor to reinforce the Agile practice of information radiators.

At this point, each team had a concept for their final product. During the next time box, the teams worked to identify constraints, such as time, Lego building skills, etc., that would help them prioritize the features of their product. The teams then worked with their customer to identify the minimal marketable product (MMP) that would deliver value within the constraints. Teams then considered whether their product was feasible – could they build their MMP within the constraints? As this was a learning project, teams discussed this point, but all teams were expected to continue with the project.

Teams next moved into the initiate phase of the Agile project, where the initial concept for the solution is refined, requirements are documented as user stories, and the stories are sized and prioritized. To support these activities, teams created user personas during the first time box in the initiate phase. Personas document the role of different groups of users, how they will use the final product, and how the product adds value to a person in this group. Teams are expected to identify and document three to five personas for their product.

Once the team has created user personas, they move to the next time box, where they write user stories to document the requirements for their product. The user stories used a common format – "As a [role], I want to [do something], So I can [achieve outcome or value]." This process was iterative. Initially, individual team members wrote user stories, then the team collaborated to combine similar stories and split large stories into smaller stories. Teams also checked that they had written user stories from the perspectives of all the personas they had identified. Finally, teams worked with the customer to review the high-level solution to ensure the user stories covered all the previously identified features and wrote additional stories as needed. Also, as user stories were revised and refined, the teams worked to capture acceptance criteria to define how they would know that a given story was complete.

At this point, the teams had a reasonably complete set of user stories for their product. In the next time block, the teams worked with their customer to prioritize the stories based on the business value using the MoSCoW (Must, Should, Could, and Won't) method (Moscow, n.d.). The prioritization process was often iterative, with teams reviewing the number of stories in each category and revising their prioritization as needed to ensure that too many stories were not prioritized as must-haves.

After prioritizing the user stories, the teams worked on estimating the work needed to build each story. Teams were reminded that the work to build a story should also include the work required to test the feature. Estimation was done by having the team agree on what they felt was the smallest story and then estimating the work for other stories relative to this story. Teams could use either story points based on the Fibonacci series (1, 2, 3, 5, 8, 13, etc.) or t-shirt sizes (S, M, L, XL, etc.). Teams estimated their "Must do" stories first, followed by "Should do" and "could do" stories to ensure that the highest priority stories were sized by the end of the time block.

Now, the teams are ready to organize their user stories into releases. At this point, teams created Agile Kanban boards with columns for release 0 and future releases. Teams were told they would have ten minutes to work on a Release 0 product and worked with the customer to identify which stories should be in the backlog for this release. The small amount of time allocated for release 0 was designed to ensure that the teams could quickly see the entire Agile iterative process of planning work, doing the work, and then showing the customer the completed work.

The teams then spent 10 minutes working on their release 0 product. "Doing" and "Done" columns were added to the team Kanban boards, and individual team members moved user stories from the release backlog to the "Doing" column, built part of the product, and then moved the user story to the "Done" column. At the end of the iteration, teams demonstrated their product to their customer, received feedback from the customer, and celebrated the accomplishments of the first iteration. After this, the team completed a retrospective on the iteration by discussing what went well, what could have gone better, and identifying ways to make improvements.

After completing the work for release 0, teams completed two more releases using the Agile iterative cycle of planning the work, doing the work, showcasing the work to the customer, and doing a team retrospective. After the second of these iterations, the teams also showcased their work to the entire class. The time allocated to each of these iterations is adjusted based on the class schedule but typically is most of an eighty-minute class meeting. During these iterations, the instructor continued circulating amongst the teams to offer suggestions and coaching. Where appropriate, for example, if several teams were experiencing the same issue, the instructor would interrupt the teams' work for a short discussion with the entire class.

Initially, the Agile Practice Project was assessed based on student participation. Students earned points equal to approximately 1 % of the course grade for participating in the practice project. Recently, two additional assignments have been added to the Agile practice project. One assignment is an online discussion where one member from each team posted their team's product idea, focusing statement, and at least two personas that the team identified. All students then read the team posts and made at least two replies to provide constructive feedback to other teams. Since all the teams are working on the same project, this activity lets students see what the other teams developed and compare and contrast them to their team's work. This assignment was completed when the teams had finished the planning work and were ready to move into the building iterations – typically at the end of the first day of the project. The second assignment that has been added is completed at the end of the project. The assignment is another online discussion, with each team having a separate discussion forum. In this discussion, each team member posts a retrospective on the team's work – what went well, what could have gone better, and any questions – along with a retrospective on their individual contributions to the team's work. Each student must read all the posts and reply to at least two of their teammates, commenting on what the person did well and providing constructive feedback. The two additional assignments are worth approximately 1 % of the total course grade.

5. DISCUSSION

The Agile Practice Project has been successfully used in over a dozen class sections of an introductory Agile course over the past few years, including both in-person and synchronous online format class meetings. The course is required for all IT majors who typically take it at the end of their first year or the beginning of their second year. The course has no prerequisites, so students from majors outside of IT regularly enroll in the course. Students who successfully complete the course earn the ICAgile ICP Agile Fundamentals certification (ICAgile, Certification, n.d.).

In this context, success means that students gained experience working with Agile practices and processes, and the teams successfully built a product they could showcase at the end of the practice project. Appendix C contains photos of actual student projects from two different course sections showing work in progress during the project. While the teams successfully completed the project, as expected, they faced challenges along the way that provided opportunities for the instructor to coach the teams in using Agile processes and practices and developing the Agile mindset. One reason that teams struggled was the short time frame of the project. Some teams would go into too much detail, and the instructor would need to prompt them to focus on delivering value for the client. For example, one team was discussing whether the parking area at their venue should be gravel or paved. The instructor prompted them to think about why they were adding a parking area, leading the team to realize that it was more important to focus on matching the size of the parking area to the number of people expected to use the venue.

Another area where instructors provided significant coaching was teamwork. Since students had limited previous experience with team projects, this was expected. During the initial project activities, the tasks were clearly defined, and supporting material was presented to remind students of previous discussions related to each task. However, some teams struggled to get started, with team members waiting for someone else to show initiative. A quick visit from the instructor to ask a simple prompting question was usually enough to get the team started. Some teams struggled to form and get organized during the short length of the practice project. For these teams, the instructor worked with the team during their end-of-project retrospective to identify actions they could take to improve team communication and interactions, and these were then used to help the team write a social contract during the beginning of the client project that followed the practice project.

An additional observation is that the students are very eager to get ahold of the Legos and start building. It is important that the instructor show the teams the Lego kits to let the teams know what resources are available for the project work. However, the instructor needs to review each team's work before allowing the team to start working with the Legos.

Several themes were found in the retrospectives students submitted at the end of the project. First, students felt that the practice project helped them better understand the Agile practices and processes covered in the first part of the course. Students also noted that completing the practice project made them feel better prepared for the client project they would complete during the second half of the course. Finally, some students noted that the practice project felt rushed, which was not surprising given the design tradeoffs discussed above.

The instructors currently using the Agile practice project do regular retrospectives to assess the project and determine what is working well and where there may be opportunities to improve or clarify the project. These retrospectives led to the development of additional assignments during the project. Other ideas currently being explored include investigating other tools to support the use of the Agile practice project in fully online course sections.

6. CONCLUSION

The Agile practice project provides students useful experience working with Agile after being introduced to Agile practices and processes in a traditional classroom setting. The practice project provides students with a low-stakes way to gain experience with Agile and build confidence in preparation for using Agile to work on a project with a real-world client. Utilizing Legos or an online building tool allows students to focus solely on the practice of using Agile processes to solve a problem rather than worrying about the specific skills needed for every task. Additionally, using a project scenario that students can envision using allows students to fully engage with the use of Agile practices and processes to define the scope and requirements for the project. Finally, the project helps students start developing an Agile mindset, which employers often mention as the most important thing they look for when interviewing candidates for positions in an Agile team environment.

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Editor's Note:

This paper was selected for inclusion in the journal as the 2023 ISCAP Conference Best Teaching Case The acceptance rate is typically 2% 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 2023.

APPENDIX A

News release used to introduce the Agile Practice Project

Project News Release

The Chamber of Commerce has commissioned and released findings of a recent survey showing that area residents and local college students alike are looking for an alternative venue for outdoor fun and entertainment. 88% of residents and 65% of college students reported that they would welcome new sources of "good clean fun" in the area.

In response to the survey, Fun Ventures LLC has formed with the goal of building a family-oriented entertainment center in the area. The entertainment center will cater to groups seeking a fun and family-oriented small-scale park. Customers include businesses, school groups, church groups, sororities and fraternities, social groups, and other organizations looking for a venue to hold group outings. The center could be open to the public on a limited basis as well.

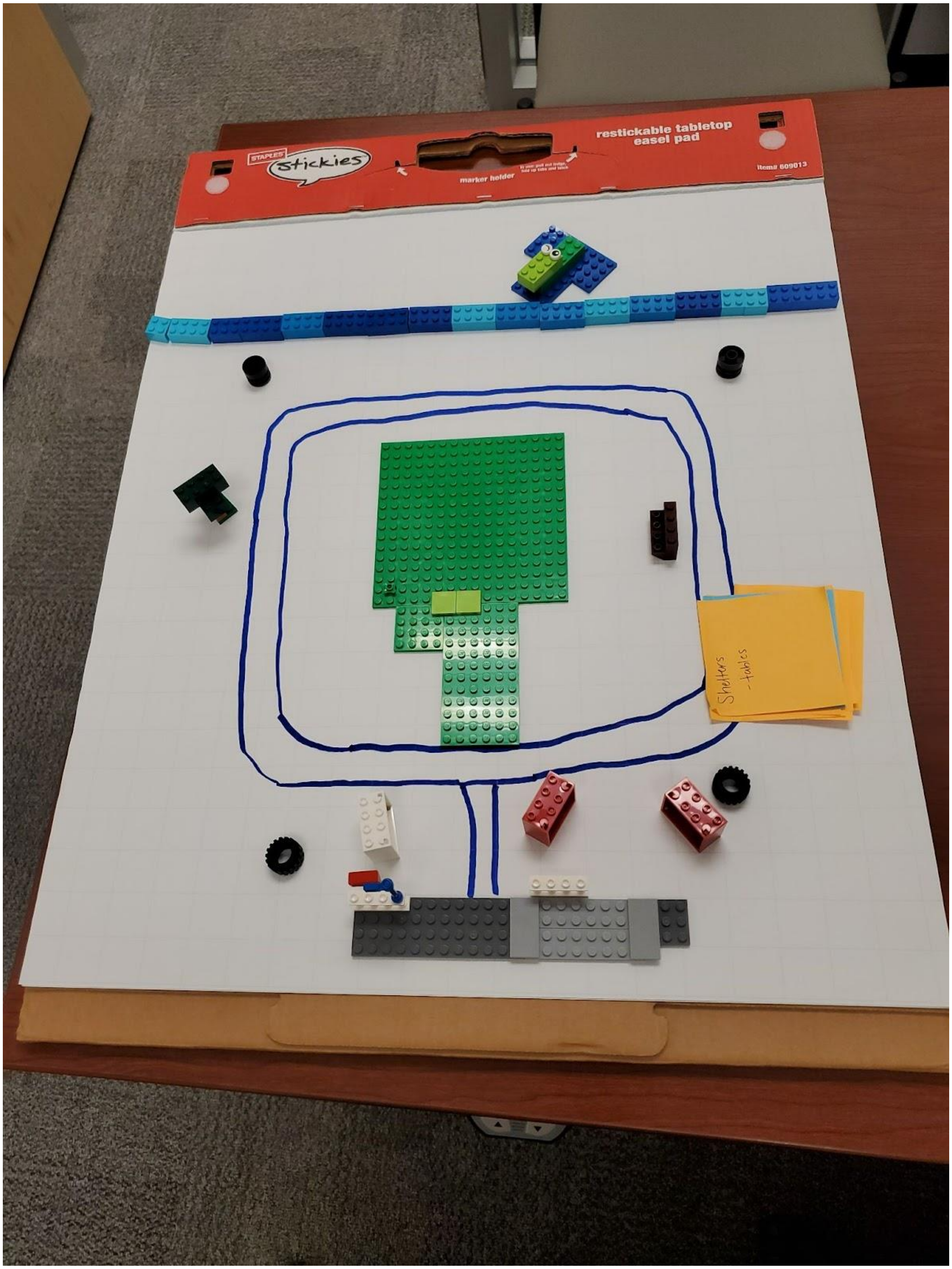
APPENDIX B

Activities and Time Allocated for concept and initiate phases of the project

Task	Time Block	Activities
Team Ideation	5 minutes	Brainstorm ideas
Select Idea	10 minutes	Use the horse race technique to select one idea
Identify Customer	1 minute	Team member who provided the selected idea is identified as the customer
Focusing question and high-level solution	10 minutes	Develop the focusing question for the project and sketch the team's planned solution
Minimal Marketable Product (MMP)	10 minutes	Determine the team's MMP and identify project constraints
Personas	10 minutes	Document personas (role, profile, and goal) for the product.
User Stories	10 minutes	Write user stories to document feature requests
Review user stories	5 minutes	Merge similar stories, split large stories, etc.
Prioritize user stories	10 minutes	Prioritize stories using MoSCoW method.
Story estimation	15 minutes	Estimate story sizes using planning poker or t-shirt sizes
Release planning	5 minutes	Group stories into release 0 and future releases
Iteration 0	10 minutes	Build features for release 0
Showcase 0	3 minutes per team	Showcase features built in release 0
Retrospective 0	5 minutes	Complete team retrospective

APPENDIX C

Photos of student work product for the Agile Practice Project




Stickies
marker holder
restickable tabletop
easel pad

Analytics for an Audience of Healthcare Professionals: Curriculum Design and Student Perceptions

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Abstract

There has been an increasing demand for healthcare analytics skills and competence by healthcare organizations. Although many universities have established programs and courses on healthcare analytics, most of these curricula have been designed for information systems (IS), information technology (IT), or analytics students. It is unclear how these curricula would fit the needs of healthcare professionals who have little IT knowledge and background yet also need analytics for their clinical or administrative job roles. This research reports on the design of an executive MBA course intended for an audience of healthcare professionals. The learning objectives, topic coverage, software tools, and assessment methods are presented along with students' perceptions of these aspects of the course. Several important lessons learned are shared and future directions are proposed, which can help other educators design similar healthcare analytics courses for professional audiences.

Keywords: Curriculum design, healthcare analytics, healthcare professionals, student perceptions, data visualization.

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Analytics for an Audience of Healthcare Professionals: Curriculum Design and Student Perceptions

Jennifer Xu and Monica Garfield

1. INTRODUCTION

Analytics is one of the two primary thematic areas in which the information systems (IS) discipline can offer tremendous help to transform healthcare through research and education (Kohli & Tan, 2016). Healthcare analytics can be used to enhance patient care, increase quality of service, reduce costs and medical errors, and improve patient satisfaction (Strome, 2013). Recent years have seen a rapidly increasing demand for healthcare analytics by hospitals and medical institutions, disease control centers, insurance companies, and other healthcare organizations (Bates et al., 2014; Zhang, 2018). Several driving forces have contributed to this trend: the need to reduce cost of care (Bates et al., 2014; Osawa et al., 2020); the availability of big health data in the form of Electronic Health Records (EHRs) and multimedia data generated by mobile devices, monitors and sensors, and social media users (Dolezel & McLeod, 2019); as well as the advancements in machine learning (ML) and artificial intelligence (AI) technologies that have enabled deep analyses of large volumes of data to discover novel patterns and knowledge (Rajkomar et al., 2019; Rajpurkar et al., 2022; Yang et al., 2021).

In response to the trend, many universities have established programs and courses with a focus on healthcare analytics (Paul & MacDonald, 2020). However, most of these courses are designed for undergraduate or graduate students who are enrolled in IS, information technology (IT), or analytics majors, aiming at careers in data science and analytics in the healthcare industry. Little pedagogical research and guidance can be found regarding the development of analytics curricula for healthcare professionals (e.g., doctors, nurses, and hospital managers), who are enrolled in non-analytics, non-IS programs (e.g., executive MBA programs) seeking to understand and use analytics to help with decision making in clinical or administrative tasks.

Healthcare professionals in such programs may be different from IS/IT and analytics students in two aspects, posing challenges on the curriculum design. First, unlike IS/IT and analytics students who often have taken some prerequisite technical courses (e.g., data processing and management courses), healthcare professionals may not necessarily have technical background and skills, especially when healthcare analytics is the only technical/analytical course in the program. Moreover, while some professionals may have received training in statistics and regression, which is fundamental to analytics, others may not be adequately prepared for data analysis. Consequently, it is difficult to determine the appropriate scope, *topic coverage*, and pacing in such a situation, if allocating introductory and advanced contents into two courses is not an option.

Second, healthcare professionals may use analytics for different purposes due to their diverse job roles and responsibilities in their organization. For instance, while doctors may hope to be able to explain to patients how algorithms work to make diagnoses, managers may have little interest in clinical analytics but only wish to visualize the organization's operational expense data. With the varying goals, it is hard to consolidate a set of *learning objectives* that meet everyone's expectations.

To address these challenges, this paper presents the design of an executive MBA course on healthcare analytics at the business school of a northeastern U.S. university. The course is one of the required courses of the program specifically oriented for healthcare professionals. We also report the feedback from the students who are employees of a world-class hospital based in the Greater Boston area. We seek to address two research questions (RQs):

- **RQ1**: What *topics* should be covered, and *software tools* be used in the healthcare analytics course?
- **RQ2**: How do students *perceive* the effectiveness of various aspects of the course (e.g., topics, tools, learning activities, assessment methods, and the fulfillment of learning objectives)?

The contribution of this research is threefold: First, this study presents the curriculum design of a healthcare analytics course for professionals enrolled in non-analytics, non-IS, executive programs. Educators seeking to design analytics courses for similar audiences may find the content topics, selected tools, and assessment methods helpful for their curriculum development endeavors. Second, we summarize lessons learned from this course and offer a few design principles. Third, the students' feedback reveals additional aspects that course designers and program developers need to consider carefully when facing a professional audience with diverse learning objectives and expectations.

The remainder of this paper is organized as follows. The next section reviews the related work. Section 3 presents the research methodology, followed by the course design components. Section 5 reports the results of the survey. Section 6 discusses the results, lessons learned, and future directions. The last section concludes the paper.

2. RELATED WORK

Healthcare Analytics

Healthcare analytics is a broad term referring to a collection of methods, tools, and techniques to "explore, analyze, and extract value and insight from healthcare data" (Strome, 2013, p. 2). One of the reasons for the increasing adoption of healthcare analytics is the fast-growing cost of healthcare. According to the World Health Organization (2023), the United States has been the most expensive country in healthcare with total healthcare expenditure counting for approximately 17% of its Gross Domestic Product (GDP). Another driving force is the wide adoption of Electronic Health Record (EHR) systems, which makes it possible to analyze medical records and histories of patients in a timely manner to identify risk factors and design effective treatment procedures (Kohli & Tan, 2016). Big data, such as mobile device and sensor data, medical imaging data, and text data, have also been analyzed and mined in order to assist with disease control and public health by monitoring the spread of viruses and infectious diseases (Xu & Babaian, 2022).

State-of-the-art analytics techniques can be used to reduce healthcare cost by identifying high-risk, high-cost patients (Bates et al., 2014; Osawa et al., 2020), reducing preventable deaths and medical errors (Corny et al., 2020), and optimizing clinical workflow (Akkus et al., 2019). In addition to traditional statistical modeling and data mining techniques such as regression analysis and decision trees, techniques based on machine learning (ML) and artificial intelligence (AI) has been widely employed to aid descriptive, predictive, and prescriptive analysis in various clinical areas (Rajkomar et al., 2019), such as prediction of diabetes and hypertension (Razavian et al., 2015), diagnosis of cardiovascular diseases (Litjens et al., 2019), and detection of cancerous tumors (Lehman et al., 2019).

Healthcare organizations, providers, and patients could benefit significantly from understanding and effectively using healthcare analytics. Many healthcare professionals wish to receive education and training from properly designed programs and courses to gain knowledge and skills, and to learn to understand, select, and use state-of-the-art analytics technologies to enhance the quality of care and reduce healthcare costs.

Curriculum Design of Healthcare Analytics

Although curriculum frameworks for healthcare informatics have been recommended by practitioners (e.g., HIMSS (2024) and CAHIIM (2024)), only a limited number of studies can be found in the literature that present the curriculum design of healthcare analytics, and the subjects and contents in these courses are rather diverse. Such curricula research typically focuses on three key issues: content topics, tools, and skill sets. For example, Dolezel and McLeod (2019) conducted a comprehensive survey with healthcare managers across the nation. They found that data mining, data visualization, and SQL are the most frequently used technologies in healthcare workplaces, and that analytics tools including SAS, IBM SPSS, Tableau, and Microsoft Power BI are the top visualization tools adopted. Paul and MacDonald (2020) presented a curriculum framework for creating new or evaluating existing analytics programs at both undergraduate and graduate levels. They identified a set of required skills (e.g., communication skills and business acumen) and recommended to incorporate into a healthcare analytics program a sequence of courses ranging from basic statistics to advanced machine learning. Zheng et al. (2014) considered the broader healthcare IT (HIT) programs and suggested bringing business intelligence and analytics components to the HIT curriculum in addition to other HIT courses such as data management, data warehousing, and EHR systems. Parks (2020) proposed to employ a contextual active learning approach to designing a healthcare analytics course in a business curriculum. By contextualizing pedagogical activities (e.g., lectures, class discussions, and assignments) in a sequence of modules related to the healthcare domain, this design approach helps better engage students and achieve the key learning objectives. Sapci and Sapci (2020) performed a systematic review of the HIT education literature and recommended integrating AI training into medical and health informatics curricula. They proposed to teach AI as a new competency and suggest three types of skills: application of AI techniques, development of AI applications, and assessments of AI limitations and validation of clinical accuracy of AI algorithms.

Nearly all these curricula are designed for IS/IT or analytics students who have already had some technical skills. It is unclear how these curricula would fit the needs of healthcare professionals who have little IT background, limited technical knowledge and skills, and diverse learning objectives. Therefore, the design of a course for this type of audience must take these differences into consideration when selecting the content topics, pedagogical and learning activities, software tools, and assessment methods.

3. METHODOLOGY

This course was part of an executive MBA program offered at a business school in a northeastern U.S. university. The program was designed specifically for healthcare professionals, and the first cohort of students came from a world-class hospital based in the Greater Boston area. Since our students had diverse job roles, expectations, and goals, the first step in our course development was to send inquiries to several student representatives to gather learning objectives (LOs), which will be presented in the next section.

To address the first research question (RQ1) regarding content topics, we did a textbook search. Unfortunately, as noted in previous research (Parks, 2020), there had been no suitable textbooks on healthcare analytics. There also was no pedagogical framework or curriculum model to follow. As a result, we compiled a set of lecture notes, based on the identified LOs (see the next section), using materials from diverse sources including data mining and business analytics textbooks (e.g., (Shmueli et al., 2016)), academic literature databases (e.g., PubMed Central, Google Scholar), and online resources (e.g., GitHub).

To answer the second research question (RQ2) regarding student perceptions of the course design, we used the survey methodology to gather their feedback. The survey was anonymous and consisted of two parts: Part A was administered in the first week of the semester and was intended to gather information about student backgrounds, demographics (e.g., age, gender), job roles, prior analytics knowledge, and learning expectations. Part B was administered in the last week of the semester and focused on student perceptions of the effectiveness of the different aspects of the course design, measured by 5-point Likert scale questions with 1 being the least favorable and 5 the most favorable option.

Questions in Part B were developed based on previous research. In particular, the ease-of-use, usefulness, and satisfaction of the course design component (e.g., topics, tools) were assessed using instruments found in technology acceptance model (TAM) research (Davis 1985). A pilot survey was conducted before the last week to validate the questions.

Appendix A provides the complete questionnaires of the two parts.

4. COURSE DESIGN

This section presents the course design regarding the learning objectives, topic coverage, tools selected, and assessments of learning outcomes.

Learning Objectives

Based on the responses from representative students (see the above section), we identified four key LOs for this course:

- LO1: To be able to *select, process, and visualize* healthcare data that are appropriate for an analytics task.
- LO2: To *understand* the methods and algorithms conceptually, and to be able to *select and use* the appropriate methods and algorithms based on the requirements of the task.
- LO3: To be able to *interpret* the results produced by algorithms and tools in the healthcare context and make decisions based on the results.
- LO4: To be cautious of the ethical issues of using healthcare analytics in decision support.

Various pedagogical and learning activities were used in this course, including lectures, in-class hands-on exercises, case studies, and class discussions.

The course was delivered as a synchronous online course on Zoom.

Week	Module	Topics	Case Studies
1	1. Basic Concepts	• Components in healthcare analytics applications • Use cases of healthcare analytics	(Bates et al., 2014; Levin et al., 2018; Morel et al., 2020; Osawa et al., 2020)
2-4	2. Data Processing and Visualization	• Healthcare data sources and data types • Data quality and data imputation • Data visualization	(Bhaskaran & Smeeth, 2014; Kahn et al., 2012; Miao et al., 2023; Weiskopf & Weng, 2013)
5-7	3. Statistical Analysis	• ANOVA • Linear regression • Logistic regression	(Bhandari et al., 2020; Skrepnek, 2005)
9-12	4. Machine Learning (ML) and Artificial Intelligence (AI)	• Decision tree • Bayesian models • Neural networks and deep learning • Natural language processing (NLP) • Image processing in radiology • Performance evaluation	(Akkus et al., 2019; Corny et al., 2020; Lehman et al., 2019; Litjens et al., 2019; Rajkomar et al., 2019; Yang et al., 2021)
13	5. Ethics of Healthcare Analytics	• Ethical and legal issues • Data privacy • Fairness and biases • Limitations of algorithms	(Balthazar et al., 2018; Burton et al., 2017; Cohen et al., 2014; Katznelson & Gerke, 2021)

Table 1: Topic coverage

Topic Coverage
Based on our review of the literature and business analytics textbooks, a set of topics were selected and organized into several topic modules: basic concepts of healthcare analytics, data processing and visualization, statistical analysis, machine learning (ML) and artificial intelligence (AI), and ethical issues. Each module consisted of one or more class meetings. Table 1 presents the topic coverage of this course.

Module 1: Basic concepts (LO1). This module provided an overview of healthcare analytics and introduced the basic concepts of analytics, such as descriptive, predictive, and prescriptive analysis. Five use cases in which healthcare analytics for quality of care and cost reduction were presented, including high-cost patients, readmission, triage, decompensation, and adverse events (Bates et al., 2014). Each use case was illustrated with a case study selected from the literature. For example, a case study on the identification of high-need, high-cost patients was used to demonstrate the potential of machine learning in reducing medical costs (Osawa et al., 2020).

Module 2: Data processing and visualization (LO1/LO3). This module introduced the diverse sources of healthcare data, including EHRs, sensor and mobile device data, images, text, videos, and audio data. Different types of data (e.g., continuous vs. categorical, structured vs. unstructured) were explained. Special attention was drawn to the data quality issue because poor data quality may lead to incorrect or misleading results causing devastating consequences to patients. Various data imputation approaches were presented for handling different types of missing data problems. A comprehensive case study was presented and discussed regarding how different data quality issues were resolved in a clinical study seeking to identify risk factors for 30-day readmission for hip fracture surgeries (Miao et al., 2023).

Students learned to use Tableau (see the next subsection on tools) to visualize healthcare data by creating various charts and dashboards. They were required to interpret the visualizations and to examine the validity of the results in the particular setting of the task based on their domain knowledge.

Module 3: Statistical analysis (LO2/LO3). Since statistics is the foundation of many analytical approaches, including machine learning (ML), this module is critical for students to understand and use any advanced techniques. Although students learned basic statistics previously, most of them were not familiar with regression. As a result, three class meetings were spent on reviewing the concepts and practicing statistical analysis using SPSS. Students learned when to use linear or logistic regression depending on whether the outcome variable was continuous or categorical, and how to interpret the results produced by the software and draw valid conclusions.

Module 4: ML and AI (LO2/LO3). This was the advanced topic module of this course. This module focused on supervised learning (i.e., classification) and introduced not only traditional ML approaches such as decision trees and Bayesian methods, but also the most up-to-date advancements in ML and AI, such as deep learning and its applications in medical image processing and natural language processing (NLP). Given the background characteristics of the students, the lectures did not put a heavy weight on the inner workings of the algorithms (e.g., back propagation in deep learning) but only gave brief conceptual descriptions of the logic underlying different algorithms. A number of case studies, such as diabetes prediction using neural networks (Razavian et al., 2015) and symptom recognition from patient narratives (Xu & Babaian, 2022), were discussed in class to demonstrate the applications of ML and AI in healthcare.

Students also learned to select appropriate algorithms based on the task and algorithm performance evaluation metrics (e.g., accuracy, sensitivity, specificity, false positive/negative rate, precision, recall, and F1 score).

Module 5: Ethics of healthcare analytics (LO4). The use of analytics for decision-making in the healthcare settings may raise various ethical and legal challenges and risks, especially when a decision is a critical one, such as diagnoses of diseases, selection of treatment options, and allocation of medical resources (Cohen et al., 2014). This module took a seminar format, in which students discussed and debated on many ethical issues based on their own observations and experiences from work.

Software Tools

Since most students did not have programming skills, we selected software tools that required no programming, including Microsoft Excel for basic data processing, Tableau for data visualization, IBM SPSS for statistical analysis, and RapidMiner for ML. These tools were quite easy to learn and use. With a few demonstrations and hands-on exercises, students became familiar with the tools and felt comfortable using them.

Assessments of Learning Outcomes

Learning outcomes were assessed using homework assignments, a midterm exam, a final project, and class participation, which accounted for 30%, 30%, 30%, and 10% of the grade, respectively.

Four assignments were given for students to practice data visualization (Module 2), statistical analysis (Module 3), traditional ML (Module 4), and deep learning (Module 4), respectively. For each assignment, students were provided with one or more healthcare datasets retrieved from public sources (e.g., Kaggle.com). Given the students' busy work schedules, each assignment was kept at an appropriate length and difficulty level so that it could be completed within 30-45 minutes.

The midterm exam was administered in week 8, and consisted of multiple-choice, short-answer, and essay questions. For the final project, students were given the option to either complete it independently or collaborate with another classmate. Students were required to select a healthcare problem they would like to study (e.g., youth obesity); acquire the datasets either from public or proprietary sources; process, visualize, and analyze the data using at least two methods; write the report and present the project in the last week.

In the last week of the semester, Part B of the survey was administered to gather student feedback.

5. SURVEY RESULTS

Student Backgrounds

Twenty-seven students who enrolled in this course participated in both parts of the survey. The sample included 5 (18.5%) males, 20 (74.1%) females, and 2 (7.4%) people who chose not to disclose gender information. In terms of age, 4 (14.8%) students were in their 20s, 7 (25.9%) in 30s, 11 (40.7%) in 40s, 3 (11.1%) in 50s, and 2 (7.4%) people chose not to disclose age information. Approximately half of the students (n=14, 51.9%) had bachelor's degrees, 11 (40.7%) had master's degrees, and 2 (7.4%) students had doctoral degrees. Most students (n=18, 66.7%) had administrative job roles in their organization, and a small number of students had other roles including clinical (n=4, 14.8%), technical (n=1, 3.7%), and support (n=2, 7.4%). Their length of tenure with the current role ranged from less than one year (n=5, 18.5%), 1-9 years (n=18, 66.7%), 10-15 years (n=1, 3.7%), to 16 or more years (n=3, 11.1%).

Nearly all students (n=26, 96.3%) took basic statistics courses previously. However, only three students knew regression analysis, and only a few students had IT knowledge or training in such subjects as database management (n=3, 11.1%), programming language (n=3, 11.1%), or analytics (n=1, 3.7%). Only one student used other analytical methods (e.g., decision trees) in addition to regression before.

Students had different learning objectives and expectations, including learning to interpret results generated by tools (n=21, 77.5%), to understand how algorithms work (n=20, 74.1%), to choose the appropriate analytics methods (n=14, 51.9%), to use the state-of-the-art methods and tools (n=14, 51.9%), to understand the limitations of different methods (n=12, 44.4%), and to increase career opportunities (n=11, 40.7%).

Perceptions of Course Design

Part B of the survey concerned students' perceptions of the course design in terms of topic coverage, learning activities, software tools, assessment methods, and fulfillment of learning objectives. We also measured their satisfaction with the course and solicited their qualitative comments.

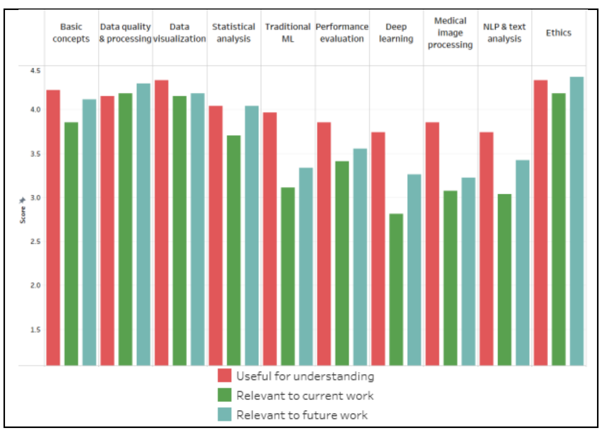

Figure 1. Topic usefulness and relevance

Topic coverage. Figure 1 presents students' perceptions of the 10 major topics in term of their *usefulness* for understanding healthcare analytics in general and *relevance* to their current and future work. It shows that students considered data visualization and the discussions about ethics the most useful topics. The average score for both topics was 4.33 out of 5.0, followed by 4.22 for basic concepts, 4.15 for data quality and processing, and 4.04 for statistical analysis. ML topics including deep learning, image processing, and NLP were considered the least useful topics with average scores below 4.0. Similar patterns are found in perceptions of relevance with ethics, data quality, and visualization being rated the most relevant and ML topics the least relevant.

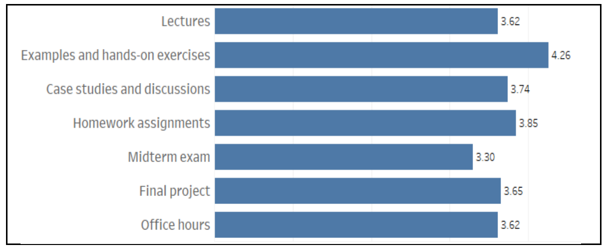

Figure 2. Usefulness of learning activities

Learning activities. Figure 2 displays student perceptions of the usefulness of various learning activities including lectures, hands-on exercises, case studies and discussions, homework assignments, midterm exam, final project, and office hours. It appears that students liked examples and hands-on exercises in class (4.26) and considered them useful for understanding the concepts and materials. The next three useful activities are homework assignments (3.85), case studies and class discussions (3.74), and lectures (3.62). They perceived the midterm exam as least useful (3.30).

Figure 3. Perceptions of the tools

Software Tools. Figure 3 presents the scores for the perceptions of software tools regarding their usefulness and ease-to-use, as well as the likelihood of using them in students' future work. Excel clearly was perceived as the most useful and easy-to-use tool likely because students all had been very familiar with Excel prior to the class. The runner up was Tableau, followed by SPSS. RapidMiner was rated the least useful and easy-to-use and also scored the lowest for future use. This could have been caused by the fact that it was only used for ML, which was perceived as least relevant by students.

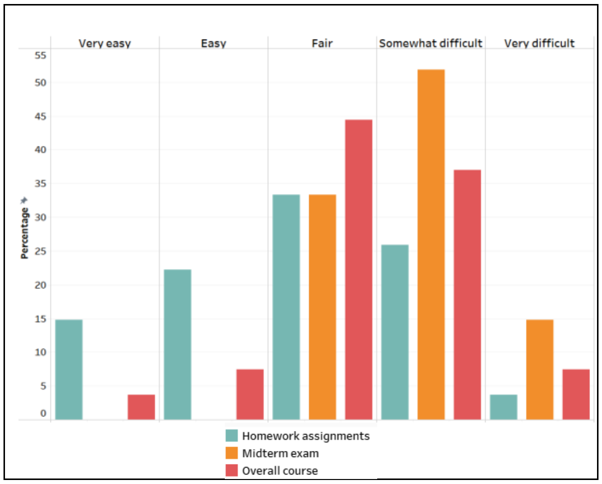

Figure 4. Perceptions of the difficulty levels

Assessments. Figure 4 shows the percentages of students with their perceptions about the difficulty levels of course work (i.e., homework assignments and the midterm exam), ranging from being very easy to very difficult. Since students had not completed their final projects by the time of the survey, we did not ask about their perceptions of the final project, but instead asked their overall impressions of the difficulty level of this course.

It appears that the distribution of the homework assignments is tilted toward the easy side, and that for the midterm is toward the hard side. More than half of the students thought the homework assignments were relatively easy or fair, 26% of the students had some difficulties with the assignments, and 3.7% found them very difficult. In contrast, only one third of the students thought the midterm was fair, and the rest of them thought it was somewhat difficult (51.2%) or very difficult (14.8%). The distribution of the overall perceptions of the course is centered on the fair (44.4%) level and the somewhat difficult level (37.0%).

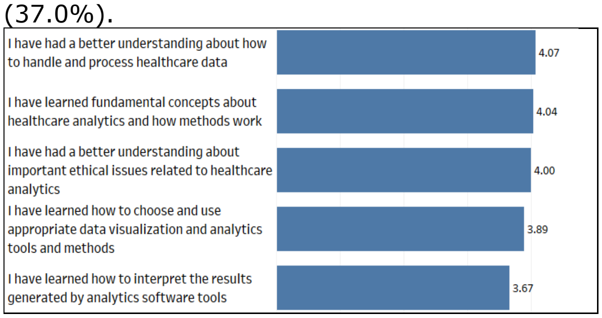

Figure 5. Fulfillment of learning objectives

Learning objectives. Figure 5 presents students' scores regarding how much they perceived that the course fulfilled their learning objectives.

Satisfactions. The average scores for the overall satisfaction of the course and the likelihood of recommending the course to others are both 4.0 out of 5.0.

Qualitative comments. Students made many comments regarding the strengths of the course and also suggested ways to improve the course design. For example, a student commented on the roles of different learning activities:

> *The homework assignments were excellent opportunities to implement what we were learning in class. The real-life examples and case studies of how someone uses these concepts professionally were very helpful. The final project is a great way to tie everything together.*

Most students enjoyed the data visualization part of the course in which they learned to use Tableau. A student put it enthusiastically:

> *I loved the Tableau dashboards and am looking to create these for a few KPIs in our billing and operations.*

A student made a very useful recommendation about how to improve the future delivery of the course by balancing the time spent on clinical and other data analyses:

> *I would suggest less of a focus on exactly how data is used in clinical care by clinicians and more on the healthcare data world as a whole. Many of us are not patient facing and that element (the actual patient care/impact) feels like a small part of the chain of data analytics.*

6. DISCUSSION

Several findings can be drawn from the survey results. First, in terms of *topic coverage*, students enjoyed data visualization the most and considered advanced topics on ML and AI less useful and relevant. This is not surprising because ML and AI have been mainly used in advanced clinical applications such as disease predictions and most students may not need these advanced techniques to analyze their data. Students also liked the discussion about ethics. Second, similar to the perceptions of topics, the perceptions of *software tools* favored Excel and Tableau, yet SPSS and RapidMiner, which were used for advanced statistical analysis (e.g., logistic regression) and ML, were perceived as less useful and difficult to use. Third, regarding *learning activities and assessments*, students preferred hands-on practices, case studies, and homework assignments, but did not like the timed midterm exam. Last, students found the course moderately difficult overall, and fulfilled most of their *learning objectives* and expectations.

Based on these findings, we summarize a few lessons learned:

- *The topic coverage should be determined based on the students' background and learning expectations*. Since this course is the only analytics course in the program, it could be too ambitious to treat introductory topics (e.g., data processing and visualization) and advanced techniques (e.g., ML and AI) equally. Students had more difficulty understanding and appreciating the logic and power of ML and AI methods, causing them to consider these topics less useful. Future deliveries of this course could allocate more class meetings to introductory topics and use just fewer classes to explore ML and AI techniques at the conceptual level.

- *The course could leverage both simple and advanced analytics tools*. Simple data analysis functionality, such as descriptive statistics, ANOVA, and linear regression, and visualization tools, such as charts and diagrams, are readily available in Microsoft Excel. Since students were already familiar with Excel, they found Excel useful and easy to use. They also enjoyed Tableau which allowed them to visualize their data using various charts and dashboards. However, they tended to find SPSS and RapidMiner intimidating due to the relatively steep learning curves for these tools. Corresponding to the topic coverage adjustments (see above), we would increase the time and use of Tableau and even other popular data visualization tools, such as Microsoft Power BI. However, we will still spend a reasonable amount of time on advanced tools such as SPSS and RapidMiner, which may be challenging for some students, to bring up the full potential of healthcare analytics.

- *Considering students' characteristics, the assessment methods need to be adjusted.* Since students were professionals in an executive education program, they may not be as accustomed to test taking as regular students. As a result, they tended to dislike typical assessment methods such as timed exams. Alternative methods, such as a take-home midterm exam may serve this audience better.

- *The course should cover a balanced set of applications of both clinical and administrative analytics*, which use different types of data and serve different purposes. Clinical applications by doctors and researchers need to use patient health records in order to identify risk factors and design appropriate intervention measures. However, hospital managers analyze operational, financial, and admission data for quality control (e.g., to identify factors that affect 30-day readmission rates) or pricing and revenue analysis purposes. With different job roles and expectations, students would need to learn different types of data analysis and applications. As noted by one student, if most of the students in the cohort had administrative roles, less time could be allocated to clinical analytics.

7. CONCLUSION

Based upon our thorough review of currently published work on the subject of curriculum design for healthcare analytics, we find that our research is unique in its focus on healthcare analytics education for professional audiences. The design aspects that we share in this paper, including topics, tools, and assessments, would be helpful for other educators to design similar courses or programs intended for healthcare professionals. In addition, the perceptions of the students and the lessons learned reveal additional aspects, expectations, attitudes toward such a course that educators may need to consider when designing courses for professional audiences.

In addition to the modifications that we will implement in the future delivery of this course, we will perform additional empirical studies to investigate how different course design factors affect student performance, perceptions, and satisfaction in this course.

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APPENDIX A

Survey Items

Attributes	Items
Age	What is your age? ○ 20-29 ○ 40-49 ○ 60+ ○ 30-39 ○ 50-59 ○ Prefer not to answer
Gender	What is your gender? ○ Male ○ Female ○ Prefer not to answer
Education	What is the highest degree you have completed? ○ Associate degree ○ Bachelor's degree ○ Master's degree ○ Doctorate degree
Job Role	What is your job role (check all that apply) in your organization? ☐ Clinical (e.g., Physician, Nurse, Surgeon) ☐ Administrative (e.g., Director, Manager, Team Leader) ☐ Technical (e.g., Radiology) ☐ Support (e.g., Educator, Analyst) ☐ Other, please specify_______________
Tenure	How long have been in your current job role? ○ Less than one year ○ 1-5 years ○ 6-9 years ○ 10-15 years ○ 15+ years
Technical Background	Have you taken any of the following courses at any institution (check all that apply)? ☐ Statistics ☐ Data science or analytics ☐ Data management ☐ Programming languages (e.g., Python, R, Java) ☐ Machine learning and artificial intelligence ☐ Other, please specify_______________
Analytical Knowledge	Have you used any of the following analytical methods in your work (check all that apply)? ☐ Regression analysis (e.g., Linear, Logistic) ☐ Bayesian models (e.g., Naïve Bayes, Belief Network) ☐ Decision tree ☐ Support vector machine (SVM) ☐ Neural networks ☐ Natural language processing (NLP) ☐ Clustering ☐ Other, please specify_______________

Learning Expectations	What objectives do you wish to achieve in this course? ☐ I’d like to learn the state-of-the-art methods and tools ☐ I’d like to understand how analytical methods work ☐ I’d like to be able to understand and interpret the resulted generated by analytical tools ☐ I’d like to learn limitations of different methods ☐ I'd like to be able to choose the appropriate methods when analyzing my data ☐ I want to increase my career opportunities ☐ Other, please specify_______________

Table 1. Survey items in Part A: Student Background

Course Aspects	Items	Measures (5-point Likert Scale)
Topics: Usefulness	Do you think that the topics are useful for you to understand healthcare analytics in general? - Basic concepts - Data quality and processing - Data visualization - Statistical analysis - Traditional ML (e.g., Decision tree, Bayesian) - Performance evaluation - Deep learning - Medical image processing - NLP & text analysis - Ethics	From useless (1) to extremely useful (5) for each topic
Topics: Relevance to Current Work	To what extent do you think the topics are relevant to your **current** work? - Basic concepts - Data quality and processing - Data visualization - Statistical analysis - Traditional ML (e.g., Decision tree, Bayesian) - Performance evaluation - Deep learning - Medical image processing - NLP & text analysis - Ethics	From completely irrelevant (1) to extremely relevant (5) for each topic
Topics: Relevance to Future Work	To what extent do you think the topics are relevant to your **future** work? - Basic concepts - Data quality and processing - Data visualization - Statistical analysis - Traditional ML (e.g., Decision tree, Bayesian) - Performance evaluation - Deep learning - Medical image processing - NLP & text analysis - Ethics	From completely irrelevant (1) to extremely relevant (5) for each topic
Tools: Usefulness	How do you rate the usefulness of the software tools we used in this course? - Excel - SPSS - Tableau - RapidMiner	From useless (1) to extremely useful (5) for each tool
Tools: Ease-of-use	How do you rate the ease-of-use of the software tools we used in this course? - Excel - SPSS - Tableau - RapidMiner	From very difficult (1) to very easy (5) for each tool

Tools: Likely to Use in the Future	How likely do you think you will use these tools in your future work? - Excel - SPSS - Tableau - RapidMiner	From not likely (1) to very likely (5) for each tool
Learning Activities: Usefulness	How do you think the following learning activities help you understand the materials? - Lectures - Examples and hands-on exercises - Case studies and discussions - Homework assignments - Midterm exam - Final project - Office hours	From useless (1) to extremely useful (5) for each activity
Difficulty Level: Homework	How do you rate the difficulty level of the homework assignments? - HW1: Data visualization - HW2: Statistical analysis - HW3: Traditional ML - HW4: Deep learning	From extremely easy (1) to extremely difficult (5) for each assignment
Difficulty Level: Midterm Exam	How do you rate the difficulty level of the midterm exam?	From extremely easy (1) to extremely difficult (5)
Difficulty Level: Course	How do you rate the overall difficulty level of the course?	From extremely easy (1) to extremely difficult (5)
Learning Outcomes	After taking this course, I feel that - I have had a better understanding about how to handle and process healthcare data - I have learned fundamental concepts about healthcare analytics and how methods work - I have had a better understanding about important ethical issues related to healthcare analytics - I have learned how to choose and use appropriate data visualization and analytics tools and methods - I have learned how to interpret the results generated by analytics software tools	From strongly disagree (1) to strongly agree (5) for each statement
Satisfaction	How satisfied are you with the course design? How likely will you recommend this course to others?	From very dissatisfied (or very unlikely) to very satisfied (or very likely) for each question

Table 2. Survey items in Part B: Student Perceptions